Decision Support Systems 93 (2017) 1–10

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Utilizing customer satisfaction in ranking prediction for personalized cloud service selection

Shuai Ding [a,b], Zeyuan Wang [a,b], Desheng Wu [c,e,*], David L. Olson [d]

[a] School of Management, Hefei University of Technology, Anhui, Hefei 23009, China
[b] Key Laboratory of Process Optimization and Intelligent Decision-Making (Ministry of Education), Hefei University of Technology, Anhui, Hefei 23009, China
[c] Economics and Management School, Chinese Academy of Sciences, Beijing, China
[d] College of Business Administration, University of Nebraska-Lincoln, Lincoln, NE 68588-4114, USA
[e] Stockholm Business School, Stockholm University, Stockholm, Sweden

ARTICLE INFO

Article history:
Received 9 March 2016
Received in revised form 14 July 2016
Accepted 5 September 2016
Available online 21 September 2016

Keywords:
Cloud service
QoS ranking
Collaborative filtering
Similarity computation
Customer satisfaction

ABSTRACT

With the rapid development of cloud computing, cloud service has become an indispensable component of modern information systems where quality of service (QoS) has a direct impact on the system's performance and stability. While scholars have concentrated their efforts on the monitoring and evaluation of QoS in cloud computing, other service selection characteristics have been neglected, such as the scarcity of evaluation data and various customer needs. In this paper, we present a ranking-oriented prediction method that will assist in the process of discovering the cloud service candidates that have the highest customer satisfaction. This approach encompasses two basic functions: ranking similarity estimation and cloud service ranking prediction that takes into account customer's preference and expectation. The comparative experimental results show that the proposed method outperforms other competing methods.

1. Introduction

Cloud service is becoming popular. Several leading IT enterprises including Google, IBM, Microsoft, and Amazon have started to offer cloud services to their customers [1], and cloud service selection now constitutes a major challenge attracting the research community to work on and investigate [2]. In the current market, multiple functionally equivalent cloud services are often available for specific domains. According to the customer type, cloud services have always been divided into two categories: the enterprise cloud services for small and medium-sized enterprises (SMEs) and the cloud apps for individual customers.

As far as enterprise cloud services (e.g. cloud storage service, data service, online file system, online backup plan), for example, the storage services on the cloud service market are offered by over 100 service vendors, which includes iCloud Storage Plan by Apple, EBS Storage Service by Amazon, Azure Storage Service by Microsoft, and others. Meanwhile, individual customers pay more attention to cloud apps deployed on open cloud platform, for example, Tencent application treasure supports more than one million apps as of April 2015, which can be classified into 32 categories, including entertainment, music, movie, news, healthcare, shopping, etc. There are more than one thousand functionally equivalent cloud service candidates in the same classification. Given the lack of cloud computing experience of non-expert customers, it is tedious to manually select an appropriate service from plenty of functionally equivalent candidates.

In recent years, cloud service selection through quality analysis has gained much attraction among service-oriented computing and cloud computing communities over the past two decades. While many SMEs employing enterprise cloud services to build their cloud-based service systems, or individual customers using apps on mobile devices, both of them are facing a challenge at the selection time: often several services offered by different vendors providing similar functional properties (i.e., "functionally equivalent"). However, customers lack appropriate, qualified, sufficient information, and benchmarks to evaluate cloud services with respect to individual preferences and market dynamics [3]. In order for organizations to reap the benefits of information technology, they must understand customer behaviors [4], Therefore, there is an increasing demand for distinguishing QoS, i.e., if and to what extent the cloud service can meet the customer requirements.

Cloud service selection models have been extensively studied by both academia and industry recently, due to their commercial value and the associated research issues. Considering the intricate relations among QoS attributes, customer preferences, and market dynamics that jointly influence perceived quality of cloud services, designing a

* Corresponding author at: Economics and Management School, University of Chinese Academy of Sciences, No. 80, Zhongguancun East Road Haidian District, Beijing 100190, China.
E-mail address: dwu@ucas.ac.cn (D. Wu).

http://dx.doi.org/10.1016/j.dss.2016.09.001

general and comprehensive analytical model is critical to service selection [5,6]. While traditional models have successfully solved many real-world problems, these models face a challenge in practice: how to recommend an optimal ranking of service candidates considering both QoS constraints and customer preferences.

In this paper, we propose an innovative ranking prediction approach for personalized cloud service selection. Instead of time-consuming and costly service evaluation, our approach is built upon the collaborative filtering technology and customer satisfaction estimation method. The remainder of this paper is organized as follows: Section 2 reviews some relevant literature. Section 3 discusses the process of cloud service selection based on ranking-oriented prediction. Section 4 presents the enhanced ranking similarity measure. Section 5 describes our service ranking prediction method, followed by the comparative experiments in Section 6. Section 7 discusses the contributions and limitations of our method. Section 8 concludes with final remarks and future prospects.

2. Literature review

Plenty of cloud service selection models are proposed by scholars, and two types of service selection models are widely studied: evaluation-focused and prediction-focused. By achieving market-relevant evaluations, customers can identify the risks and benefits of each service candidate and choose the best for adoption. The most analyzed examples of evaluation-focused models include: AHP-based cloud service ranking model [7], QoS-aware service selection model [8], brokerage-based service selection approach [9], trust and reputation models [10], service selection probabilistic model [11], and sequential information considered approach [12]. Although these models seek to provide an accurate and exhaustive service measurement, their implementation involves a time-consuming and costly service testing process.

Instead of real-world service invocations, the prediction-focused models produce QoS values or service ranking by collaborative filtering (CF) [13]. In a prediction process, similar neighbors (customers or services) are identified to provide collaborative information. Popular choices for similarity estimation include Pearson correlation coefficient (PCC) [14] and vector similarity (VS) [15]. In some cases, these ratings-oriented similarity measures do not work well since many customers are reluctant or unable to present ratings. To address this problem, Kendall rank correlation coefficient (KRCC) [16], Spearman rank correlation coefficient [17], and AP correlation coefficient [18] are proposed to calculate the similarity between two rankings of the same items.

In reality, under conditions of sparse rating data, rating-oriented approaches have difficulty guaranteeing accurate ranking prediction. Cloud service selection is of necessity made without ample data due to its recency. Moreover, customers usually prefer sorting to rating because of the diversity and specificity of individual rating preference. To solve these problems, many ranking-oriented approaches have been introduced. In Ref. [19], the authors propose a novel ranking-oriented approach called RPU (ranking with prediction uncertainty), which utilizes posterior rating distribution and confidence level of prediction as two key factors for prediction uncertainty. Liu et al. [20] applied KRCC to measure the similarity of different rankings, and also offered a greedy order algorithm and a random walk model for producing an optimal ranking solution. Zheng et al. [21] presented two ranking-oriented CF approaches to enhance the performance of service ranking prediction.

It is worth noting that the customer's attitude and expectation towards service quality has not been considered in these models. Thus, we will here combine ranking-oriented prediction approach and with a customer satisfaction estimation approach to develop a novel personalized cloud service selection model.

3. Cloud service ranking prediction and selection

As there has been an exponential growth of cloud services released on the Internet, service selection techniques like QoS-aware CF approaches have become more and more important and popular [22–24]. An increasing number of SMEs prefer to deploy their services on an open cloud platform, which not only strengthens the normalization but also reduces the cost. For individual customers, various applications on standard cloud platforms provide convenience for their lives. In this paper, instead of a ratings-oriented approach, we focus on deploying the cloud service ranking prediction method (named as CSRP), which covers the similar neighbor identification, the attribute utility derivation, the customer satisfaction estimation, and the ranking prediction.

Actually, without sufficient assessment QoS data, accurate cloud service selection cannot be obtained for both SMEs and individual customers. To attack this challenge, our proposed CSRP method seeks to predict the optimal service candidates ranking by integrating the ranking-oriented prediction and customer satisfaction estimation technologies. In general, employing CSPR in cloud service selection is broken into a set of individual tasks. As shown in Fig. 1, our proposed CSRP method can be expressed in the following two steps:

Step 1 When the raw data (i.e. QoS dataset relating to service candidates) is obtained, the KRCC similarity calculation of service candidates and the significance analyzation of neighbors' ranking need to be conducted to generate the total similarity of service ranking.

Step 2 Once the new ranking similarity is generated, the top-k similar candidates' service ranking can be selected. In addition, the customer satisfaction of the cloud services are discovered and thus the optimal service ranking considering customer perception will be produced by resolving the ranking prediction optimization problem.

It is worth noting that the customer satisfaction that operates on his/her attitude and expectation towards service quality is integrated in

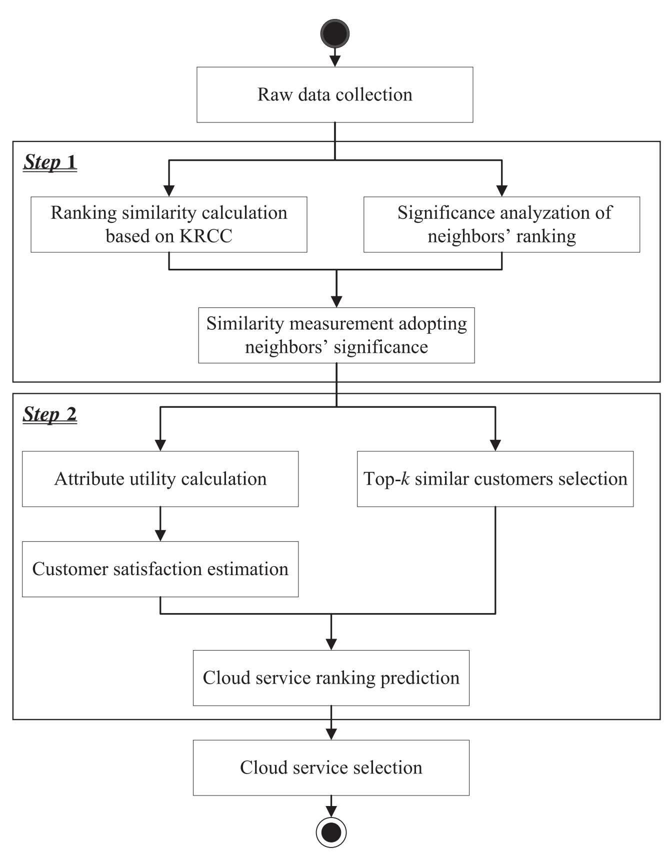

Fig. 1. The process of cloud service selection based on ranking prediction.