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Mobility and Dependence-aware QoS Monitoring in Mobile Edge Computing

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Abstract

Mobile edge computing is a new computing paradigm that performs computing on the edge of a network. It provides services to users by deploying edge servers near mobile devices. Services may be unavailable or do not satisfy the needs of users due to changing edge environments. Quality of service (QoS) is commonly employed as a critical means to indicate qualitative status of services. It is particularly important to monitor QoS of services timely and effectively in the mobile edge environment. However, user mobility and dependencies among QoS values often cause the monitoring results to deviate from the real results in the mobile edge environment. Existing QoS monitoring approaches have not taken into account these problems. To address the problems, this paper proposes ghBSRM-MEC (Gaussian hidden BayeSian Runtime Monitoring for Mobile Edge Computing), a novel mobility and dependence-aware QoS monitoring approach for the mobile edge environment. This approach assumes that the QoS attribute values of edge servers obey Gaussian distribution. It constructs a parent property for each property, thus reducing the dependence between properties. During the training stage, a Gaussian Hidden Bayesian classifier is constructed for each edge server. During the monitoring stage, combining with a KNN algorithm, the classifier is changed dynamically based on user mobility to realize QoS monitoring in the mobile edge environment. The experimental results validate the feasibility, effectiveness, and efficiency of ghBSRM-MEC.

Index Terms—Cloud computing; mobile edge computing; QoS; monitoring; Bayesian classifier; K-nearest neighbor.

Abstract
Mobile edge computing is a new computing paradigm that performs computing on the edge of a network. It provides services to users by deploying edge servers near mobile devices. Services may be unavailable or do not satisfy the needs of users due to changing edge environments. Quality of service (QoS) is commonly employed as a critical means to indicate qualitative status of services. It is particularly important to monitor QoS of services timely and effectively in the mobile edge environment. However, user mobility and dependencies among QoS values often cause the monitoring results to deviate from the real results in the mobile edge environment. Existing QoS monitoring approaches have not taken into account these problems. To address the problems, this paper proposes ghBSRM-MEC (Gaussian hidden BayeSian Runtime Monitoring for Mobile Edge Computing), a novel mobility and dependence-aware QoS monitoring approach for the mobile edge environment. This approach assumes that the QoS attribute values of edge servers obey Gaussian distribution. It constructs a parent property for each property, thus reducing the dependence between properties. During the training stage, a Gaussian Hidden Bayesian classifier is constructed for each edge server. During the monitoring stage, combining with a KNN algorithm, the classifier is changed dynamically based on user mobility to realize QoS monitoring in the mobile edge environment. The experimental results validate the feasibility, effectiveness, and efficiency of ghBSRM-MEC.
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Introduction

MObile edge computing (MEC) [1] is an emerging technology, which provides services by deploying an edge server (e.g., firewall, router, or similar devices) near mobile clients (e.g., smartphones, sensors, or similar edge ends), and between mobile clients and cloud servers. It features short response time and fast processing speed [2]. With the continuous development of various novel technologies, Web services are increasingly being applied in many fields of people’s lives, including business, manufacturing, healthcare, entertainment, etc [3]. On the one hand, the number of Web services deployed in cloud servers is growing rapidly. On the other hand, these services are gradually moved to edge servers, i.e., mobile edge services, which reside in nearby edge servers to serve users. Different service providers may provide services with similar functions, and the performance of the same services may vary in different edge servers. How to select an appropriate service that meets the needs of users has therefore drawn many researchers’ attention [4]. Thus, the concept of QoS (Quality of Service) is introduced. QoS represents the a set of non-functional attributes of services, including response time, throughput, reliability and availability, etc [5]. Users expect to select mobile edge services with guaranteed QoS. The QoS information of a service is usually disclosed by its service provider. Some providers may provide false QoS information to mislead users. This false information cannot be employed to objectively evaluate services. Therefore, to objectively and correctly evaluate the operation of services, it is particularly important to monitor QoS attributes timely and effectively at runtime [6], [7], [8]. Monitoring is one of the most effective ways to verify whether a service is valid at runtime [9]. In general, QoS attributes can be expressed by probabilistic quality attributes [10]. For example, response time can be described as “the probability that a service’s response time for a customer’s request is less than 3.6 seconds is more than 80%”. The problem of QoS monitoring is therefore transformed into the probabilistic calculation and analysis whether the collected runtime information satisfies pre-defined QoS requirements. Based on the probabilistic quality attributes, researchers have proposed many QoS monitoring approaches in traditional network environments, respectively from the perspectives of probability calculation [11], traditional hypothesis testing theory [12], [13], [14], and Bayesian theory [15], [16], [17]. However, the existing approaches are infeasible in mobile edge environments due to the following two major problems.

Existing System

It is particularly important to monitor QoS of services timely and effectively in the mobile edge environment. However, user mobility and dependencies among QoS values often cause the monitoring results to deviate from the real results in the mobile edge environment. Existing QoS monitoring approaches have not taken into account these problems. To address the problems, this paper proposes ghBSRM-MEC (Gaussian hidden BayeSian Runtime Monitoring for Mobile Edge Computing), a novel mobility and dependence-aware QoS monitoring approach for the mobile edge environment.Therefore, there might exist dependence among the QoS values of same services from same edge servers invoked by proximate users. Existing QoS monitoring approaches neglect the influence among QoS values. They assume the QoS values are independent of each other, which may cause judgement delays on service monitoring results.The existing QoS monitoring approaches assume that the current monitored QoS is irrelevant to the historical samples in S2. This would greatly reduce the monitoring probability that Bob’s requirement is met, and thus might lead to the delay or deviation of the monitoring results.

Proposed System

In summary, the main contributions of this paper are described as follows:

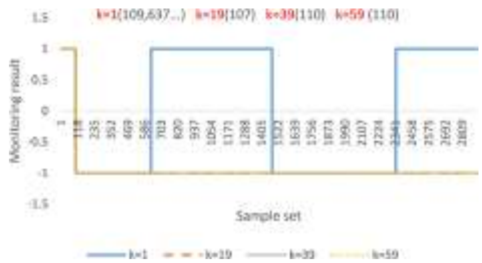
We devise a novel QoS monitoring approach considering user mobility and edge server differences in mobile edge environments. A Bayesian classifier is constructed for performing monitoring in each edge server. The classifiers can be switched dynamically adapting to user mobility. The classifiers reference QoS information from peripheral servers based on the KNN algorithm for monitoring.

We design an effective method to lessen the impact of QoS attribute value dependence on monitoring results. A parent attribute is established for each QoS attribute to construct a hidden Bayesian classifier to reduce the dependence among QoS attribute values. It is also able to address the problem of service failure detection delays caused by traditional Bayesian classifiers.

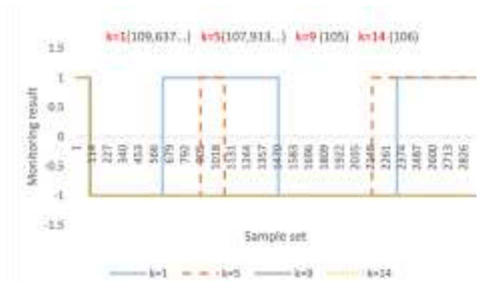
We design a series of experiments to comprehensively validate ghBSRM-MEC. By fusing a Shanghai Telecom data set 1 and a traditional QoS data set 2 , we obtain a mobile edge dataset applicable for edge QoS monitoring evaluation. The experimental results show the feasibility, effectiveness, and efficiency of the ghBSRM-MEC approach. It also proves that ghBSRM-MEC outperforms state-of-the-art approaches."

Conclusions And Prospects

Traditional QoS monitoring approaches do not consider user mobility and data dependency, which might lead to deviation in monitoring results. In this paper, we present ghBSRM-MEC, a novel QoS monitoring based on Gaussian hidden Bayesian classification in the mobile edge environment. The experiments on real and simulated data sets show that the proposed method is feasible and effective.



a



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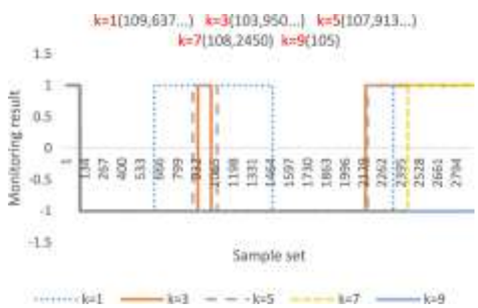

c

Effect of *K* for edge server 25 in different ranges:

(a) k=1~59, (b) k=1~14, (c) k=1~9.

For future work, the following directions will be con- sidered: First, we will further explore the impact of *k* on monitoring performance when there is no relevant historical data in monitored servers. Second, since multivariate QoS attributes [50] may contain conflicts, we will consider how to monitor multivariate QoS attributes simultaneously in mobile edge environments.

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