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# Context-aware end-to-end QoS qualitative diagnosis and quantitative guarantee based on Bayesian network

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ABSTRACT

To support Quality of Service (QoS) management on current Internet working with best effort, we propose a systematic approach for end-to-end QoS qualitative diagnosis and quantitative guarantee. Both QoS metrics and contexts of a service are considered in a comprehensive manner in our approach, which consists of three sequential stages: context discretization, QoS qualitative diagnosis and QoS quantitative guarantee. Based on Fuzzy set, an automatic unwatched discretization algorithm for discretizing continuous numeric-value is brought forth to reshape these QoS metrics and contexts into their discrete forms. For QoS qualitative diagnosis, causal relationships between a QoS metric and its contexts are exploited with the help of K2 Bayesian network (BN) structure learning by treating QoS metrics and contexts as BN nodes. A QoS metric node is qualitatively diagnosed to be causally related to its parent context nodes. An ordering method is proposed to arrange orders for nodes involved in K2 algorithm. To guarantee QoS quantitatively, those causal relationships are next modeled quantitatively by BN parameter learning. BN inference is referred to calculate the marginal on a QoS metric node given its tunable parent context nodes. Then, the QoS metric is guaranteed to a specific value a user demands with certain probability by tuning its causal contexts to suitable values suggested by BN inference, that is, QoS quantitative guarantee is reached by now. Simulations, on a peer-to-peer (P2P) network, about the above three sequential stages are discussed and our approach is validated to be soundable and effective. We also argue that our approach can be reached in a polynomial time complexity in practice.



## 1. Introduction

Current Internet delivers services merely with its best efforts; Quality of Service (QoS) is only supported or guaranteed as much as possible. There are some reasons for this awkward situation. First, it is not easy to trace, locate and identify the causes of a QoS violation on the volatile Internet. Second, even if this problem is fixed up, other problems may arise, for example, for security consideration, integrated service providers (ISPs) are unwilling to open interfaces to customers or other ISPs to fine-tune or improve QoS. Third, not all hardware on current Internet can fully support QoS managements claimed in some protocols like DiffServ [1] and so on. Besides, to support QoS managements, packets have to flow through more procedures, which will decrease the efficiency of these public facilities.

End-to-end QoS management [2] is one way to overcome these problems since customers have full controls of endpoints; hence, parameters of these endpoints can be manipulated to support QoS management. In addition, end-to-end QoS managements do not force underlayers to support QoS management; therefore, the efficiency of those public facilities will not be affected. Nowadays, overlay networks are widely used to meet the active demands for multimedia services and end-to-end QoS managements are claimed to be supported on those overlay networks. In this study, we will discuss two aspects of QoS management: QoS qualitative diagnosis and QoS quantitative guarantee, on a peer-to-peer overlay network.

QoS diagnosis is usually intended to identify QoS violations [3]. In our approach, we believe causal relationships lie between a *QoS metric* and its *contexts* [4] this metric residing in. In this study, we mainly deal with primary contexts, e.g. application *configurations*, and runtime contexts, like *the number of neighbors* or *buffer map size* of a peer in a P2P network. We call these contexts as "soft" contexts with respect to traditional "hard" contexts such as *temperature*, *location* and so on. These contexts can be viewed as the causes of the QoS metric since the QoS metric changes along with these contexts. Naturally, we refer QoS qualitative diagnosis to qualitatively identify these causal relationships between a QoS metric and its contexts. In this study, we employ Bayesian network (BN) [5] to exploit these causal relationships as BN is a common approach for representing causal relationships.

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QoS guarantee tries to satisfy users' QoS requirements and maintain a QoS metrics on user demanded levels. When the causes of a QoS metric are qualitatively identified by QoS diagnosis, we will show that users' QoS requirements can be quantitatively fulfilled by tuning these causes or contexts to guarantee the QoS metric. This quantitative guarantee is facilitated by the quantitative representation of BN for causal relationships.

Before QoS qualitative diagnosis and QoS quantitative guarantee, QoS metrics and contexts should be discretized first because both BN structure learning and BN parameter learning from continuous variables are time–space consuming tasks. Moreover, redundant relationships may be learned from continuous variables. We will discuss these problems in details in Section 3.1.

In this study, we validate our approach on a P2P streaming overlay network scenario through a simulator. We would like to point out that our approach is applicable to more generalized situations or applications because our approach is about a common technique-neutral methodology.

Our approach is estimated to have a polynomial time complexity when the number of contexts and QoS metrics involved is held in the order of magnitudes of ten. That is to say our approach is feasible to be put into practice.

To sum up, the main contributions of our approach are listed as follows:

1. Firstly, we proposed a systematic approach to qualitatively diagnose QoS and to quantitatively guarantee QoS for the first time. Besides, this approach is a general or common one, which means it is applicable to diagnose and guarantee end-to-end QoS. Our approach can migrate from situations of this study to other applications simply by replacing contexts and QoS metrics of this study with those of target applications.
2. Secondly, we put forward an automatic unwatched discretization algorithm based on Fuzzy set, i.e. Algorithm 2, for discretizing continuous numeric-contexts, which usually follow approximate Gaussian distribution.
3. Thirdly, BN structure learning (K2 algorithm) is employed to exploit causal relationships between contexts and QoS metrics, and a child QoS metric is qualitatively diagnosed to be caused by some parent contexts according to the learned BN structure. An original node-ordering method (see Section 3.2), is proposed to arrange orders for nodes involved in K2 algorithm.
4. Fourthly, BN parameter learning is then used to model those causal relationships quantitatively, and a QoS metric can be guaranteed to a quantitative value by tuning its causal contexts to their corresponding quantitative values according to BN parameter learning. To the best of our knowledge, this is the first work that investigates end-to-end QoS qualitative diagnosis and quantitative guarantee in a systematic way.

The remainder of this paper is arranged as follows: a brief summary about related works will be given in Section 2. Our approach will be illustrated in details in Section 3. Simulations and validations will be discussed in Section 4. Section 5 argues the time complexity of our approach. At last, in Section 6 we will make a conclusion about our approach.

## 2. Related works

For QoS diagnosis, traditional rule-based methods [6] require detailed margins of QoS parameters; hence, their scalability and efficiency are not satisfying. To overcome these problems, an end-to-end approach for QoS management was put forward in [3] to diagnose QoS violations. It first uses a set of end-to-end flow traffic statistics to describe a QoS violation; then, neural network techniques are referred to identify QoS violations from disturbed patterns by classifying these traffic statistics. Nevertheless, learning examples required by neural network grow with the number of possible patterns to diagnose. Besides, pattern recognition engine should be carefully trained so as not to be over-trained in case of generalization problem.

Although DiffServ architecture [1] supports end-to-end QoS guarantee, only a limit number of static QoS classes are provided. Obviously, it can not meet the active fine-grained QoS demands of diverse services. Moreover, end-to-end QoS guarantee by DiffServ may require underlying hardwares to support QoS guarantee, which will introduce overhead to those core devices and lead to low efficiency. In addition, fine-grained QoS quantitative guarantee is difficult to be realized in this architecture because these fine-grained QoS violations are hard to be traced among ISPs due to commercial security problem.

Moreover, current research [6,3] on QoS diagnosis or QoS guarantee focused mainly on one specific criteria such as *packet-loss-rate*, *packet delay* and *delay jitter* etc. on one application. In fact, other factors i.e. contexts in this study from different resources should be taken into account in a comprehensive manner because of their joint effects on a QoS metric.

Many researches had been done on continuous attributes discretization for a decision table [7–11], and many methods, e.g. MDPLC, FUSINTER and CHI-MERGE [7], had been proposed to discretize continuous attributes of a decision table. Nguyen and Skowron [10] presented an approach based on rough set and Boonlean reasoning to discretize continuous attributes. Holte [11] used one-rule-discretizer to deal with continuous attributes discretization. These methods were intended to synchronously discretize the attributes w.r.t. the decision attribute of a decision table, that is, continuous attributes are discretized in an interdependent manner. Our approach proposed in this study can discretize a continuous context independently. Another philosophy to discretize a continuous attribute is to divide a continuous attribute into equal interval slots, each of which represents a discrete value. Experts are involved in this type of approach to guide the division of the continuous attribute; Obviously, the result of this type of approach may be different from expert to expert.

## 3. Proposed approach

In general, a QoS metric changes along with the contexts it resides in, for example, in a live streaming system, mosaics will show up when *packet-loss-rate* is becoming high. Packet-loss-rate, a *QoS metric* by our approach, is usually caused by network congestion, a *context* of *packet-loss-rate* by our approach. Network congestion in turn may be caused by some other bandwidth greedy applications e.g. BitTorrent (BT) spawned applications, whose packet transport protocol like UDP, another *context* by our approach, may also be relevant to the *packet-loss-rate* QoS metric because no congestion control is built in User Datagram Protocol (UDP); as a result, bandwidth is preempted by these greedy applications. Our approach takes all contexts into consideration in a comprehensive manner to exploit causal relationships between these contexts and the QoS metric by QoS diagnosis. These contexts having causal relationships with a QoS metric are called "causal contexts". Then, these causal contexts are tuned to appropriate values to quantitatively guarantee users' requirements by QoS guarantee. Procedures of our approach are summarized in Fig. 1. Before diagnosis and guarantee, contexts are first reshaped into discrete values in order to be smoothly processed by BN toolkits.

### 3.1. Context discretization

Context values may be continuous or discrete because they may come from different applications or have heterogeneous sensor