A SURVEY FOR REAL-TIME NETWORK PERFORMANCE MEASUREMENT VIA MACHINE LEARNING

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ABSTRACT

Real-Time Networks (RTNs) provide latency guarantees for time-critical applications and it aims to support different traffic categories via various scheduling mechanisms. Those scheduling mechanisms rely on a precise network performance measurement to dynamically adjust the scheduling strategies. Machine Learning (ML) offers an iterative procedure to measure network performance. Network Calculus (NC) can calculate the bounds for the main performance indexes such as latencies and throughputs in an RTN for ML. Thus, the ML and NC integration improve overall calculation efficiency. This paper will provide a survey for different approaches of Real-Time Network performance measurement via NC as well as ML and present their results, dependencies, and application scenarios.

Keywords: Real-Time Network · Time-Sensitive Network · Machine Learning · Network Calculus

1 Introduction

1.1 Motivation

Many scheduling algorithms in Real-Time Network rely on accurate performance estimations to adjust their operating strategies. The static performance estimations cannot adapt to the dynamic network changes and learn from the network feedback. The machine learning based approaches can eliminate these constraints via historical training data. The latency, throughput and reliability are the main performance indexes to be investigated. Network Calculus provides a formal framework to estimate the performance indexes. Thus, leveraging machine learning and Network Calculus can improve the Real-Time network performance measurement.

1.2 Contribution of This Survey Article

In this survey article, we make the following contributions:

- We survey and classify advantages of ML-based network performance measurement in Real-Time Network.
- We discuss ML-based Real-Time Network architectures.
- We provide an in-depth discussion on ML strategies for network performance measurement.
- We outline open issues, challenges, and future research directions related to ML-based network performance measurement.

1.3 Article Structure

The paper is organized as follows: Comparison with related survey articles is presented in Section 2. Section 3 and Section 4. In the same sections, we also highlight the architectures for ML-based network performance measurement and ML strategies of network performance measurement. Moreover, case studies on the use of ML in network performance measurement are also presented in those sections. Issues, challenges, and future research directions are mentioned in Section 5. Finally, Section 6 concludes the paper.
2 Latency

Many RTN applications require deterministic bounds on the end-to-end delay. Network Calculus (NC) is an iterative analysis framework for the derivation of delay bounds. The models and analysis tools from NC generate all steps towards the derivation of delay bounds. However, Kiefer et al. [2010] showed that this method suffers from the vast computational effort. The cost of delay analysis increases fast with the size and complexity of a network. Neural networks for graphs have recently been introduced to map network topologies and flows to graphs. This approach has been used in a variety of domains such as performance evaluation of networks with TCP flows Geyer [2017], routing protocols Geyer and Carle [2018], or basic logical reasoning tasks and program verification Li et al. [2016].

One example in Geyer and Carle [2018], each server is represented as a node in the graph, with edges corresponding to the connections between servers. Each flow is represented as a node with edges connecting it to the path of traversed servers. The method to transferring those graph inputs for a neural network was able to process any general graphs. The authors demonstrated this method via a numerical evaluation and showed that it can be used at a small computational cost compared to traditional network analyzes. The other example uses machine learning to estimate service curves from measurements Geyer and Bondorf [2020]. Through service curves, the correct bounds on the worst-case flow delays and inferences cannot be computed precisely due to uncontrollable uncertainties introduced by measurements. But the authors implemented an iterative method to adaptively change the probe rate and improve accuracy by reducing bias and variability.

3 Reliability

Nowadays, mission-critical applications had been widely discussed over the world. These applications rely on RTN to provide a higher level of Quality of Service (QoS). Reliability (loss) is one of the significant parameters to estimate the QoS within the RTN. For instance, the network traffic management algorithms (such as connection control, flow control) require the loss analysis to make its scheduling decision Bannour et al. [2018]. Due to larger and more complex RTN development, the size and complexity of the loss estimation grow rapidly. On the other hand, the difficulty in applying NC in realistic network scenarios is that links (or servers) may be unreliable and some packets are lost. Some NC loss analyses have proposed in Gulyas and Biro [2006] and Deng and Lin [2010] seek to estimate the packet loss from expectations instead of probabilities. But the above methods cannot adapt to the scalable network changes. One earliest work was introduced in Wang et al. [2013]. The authors modeled unreliable networks using the stochastic NC and integrated the model with a retransmission-based loss recovery. From their numerical experiment, a small number of retransmission attempts already lends RTN to a delay bound’s blow-up. Another related work in Scheffler et al. [2018] investigates reliability and NC performance within an RTN. The authors figure out that the RTN suffers from reliability and reproducibility issues during the NC computation and improved the NC performance by parallelizing its computation procedure. However, to the best of the authors’ knowledge, the state-of-the-art research on reliability investigation only via NC. Therefore, machine learning and NC become a new subject of interest to investigate the tradeoff between accuracy and scalability of a loss analysis.

4 Throughput

Under given delay constraints, the traffic carrying capacity (throughput) of RTN is another fundamental index for network management. Fei Yu and Krishnamurthy [2006] Fidler [2010] NC is a more general theory that has been applied to predict the traffic carrying capacity of RTN. The goal of throughput estimation is to infer the available throughput of a network path using only external observations of data packets. To model the minimal available throughput, we should find the tightest link which has the smallest capacity. In addition, the end-to-end available throughput of a network path is determined by the tightest link in the path. If the rate of the cross-traffic dynamically changes during an estimation, or some packets are randomly lost and then retransmitting, the corresponding estimates are imprecise.

In Khangura et al. [2019], Yin and Kaur [2016] the authors train a neural network using vectors constructed by packets. The vectors contain the available bandwidth of the packet dispersion. The neural network can generalize non-locally which kernel or ensemble machines with standard generic kernels are not able to do. It can recognize complicated functions even in the presence of noise and variability.
5 Challenges and Future Research Directions

Aiming at an optimal balance between the feasible resource allocations and offloading, the network operators must have a deep understanding of network conditions. This not only calls for accurate models but also further raises the computational complexity.

Future research should generate much interest and progress with respect to ML extensions for reliability and throughput measurements. On the other hand, NC tools development is also one potential direction for next-generation RTNs. Tool support for network calculus has not been addressed by the prior-art and brings about a new interesting perspective that can accommodate the RTN loss during the measurement.

6 Conclusion

The real-time network is required for next-generation communication. To achieve the stringent goals of real-time network, network operators rely on an efficient, reliable, flexible, and globally network performance measurement, which helps to assist real-time networks in providing these services promptly. The complex measurement becomes a resource intensive mission while the network size increasing. ML can help to form the basis for network performance measurement. Moreover, by applying ML in network performance measurement, efficiency and resiliency can potentially be improved.

In this survey article, we have comprehensively covered the advantages of ML-based network performance measurement. We have then discussed case studies on the use of network performance measurement with ML. Finally, we have identified and discussed challenges, issues, and future research directions related to ML-based network performance measurement before concluding the paper.

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