Poster: A Distributed Reinforcement Learning Approach for Energy and Congestion-Aware Edge Networks

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ABSTRACT
The abiding attempt of automation has also pervaded computer networks, with the ability to measure, analyze, and control themselves in an automated manner, by reacting to changes in the environment (e.g., demand) while exploiting existing flexibilities. When provided with these features, networks are often referred to as "self-driving". Network virtualization and machine learning are the drivers. In this regard, the provision and orchestration of physical or virtual resources are crucial for both Quality of Service guarantees and cost management in the edge/cloud computing ecosystem. Auto-scaling mechanisms are hence essential to effectively manage the lifecycle of network resources. In this poster, we propose Relevant, a distributed reinforcement learning approach to enable distributed automation for network orchestrators. Our solution aims at solving the congestion control problem within Software-Defined Network infrastructures, while being mindful of the energy consumption, helping resources to scale up and down as traffic demands fluctuate and energy optimization opportunities arise.

CCS CONCEPTS
- Networks → Network algorithms; Computer systems organization → Redundancy; Computing methodologies → Reinforcement learning.

KEYWORDS
reinforcement learning, self-driving networks, auto-scaling

ACM Reference Format:

1 INTRODUCTION
Recent advantages in artificial intelligence (AI) and machine learning (ML) are paving the path to autonomous and self-driving networks: networks that measure, analyze and control themselves in an automated manner, reacting to changes in the environment,
With the network partition, the controller supervises a subset of switches and communicates with the other controllers to obtain a consistent network view.

The decision logic is the fruit of a (self-)learning process, built upon the reinforcement learning (RL) framework. In our solution, each RL agent uses the one-step Q-learning algorithm [9]. Figure 1 shows the components and functionalities involved during the process. The agent interacts with the underlying network and performs actions, where each action is associated with a reward. The reward function mimics the objective of reducing the energy cost and catering to the application requirements. We model this in the reinforcement learning problem, whose actual goal is to maximize the long-term discounted reward per action.

The agent collects the statistics and combines them with previous historical data. Data are then passed to the optimizer module, which enforces the RL process and outputs the best possible strategy. The action set consists of a list of binary variables denoting the subset of switches and links to activate or deactivate. The agent interacts with the underlying network and performs actions, where each action is associated with a reward. The reward function mimics the objective of reducing the energy cost and catering to the application requirements. We model this in the reinforcement learning problem, whose actual goal is to maximize the long-term discounted reward per action.

When the demand peak is passed, the system powers off a subset of switches and links to reduce energy consumption and accommodate traffic demand. The decision logic is split across multiple controllers to improve the management of a large quantity of information needed for accurate actions. We expect that our system will enable both high application satisfaction and minimal management costs when deployed over more challenging environments. Future steps will include extensive evaluation of Relevant’s behavior in these contexts and an in-depth analysis of the learning process.

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REFERENCES


