Poster: Towards Learning-Based Medium Access Channel

Mohammad Sepahi

ABSTRACT

Networking protocols are used by each networking host (e.g., end device) to communicate with one another. These hosts Before can exchange data bit with the central node (e.g., Base Station (BS) or Access Point (AP)), should first negotiate the communication protocol, conditions and parameters for that transmission which is supported at the protocol stack. Estimating these parameters in an intelligent way is much needed desired. Could machine learning estimate the parameters on their own without human in the loop? In this paper, we investigate the medium access control protocol in cellular networks. We demonstrate that reinforcement learning.

KEYWORDS

Medium access control, MAC protocol, reinforcement learning

1 INTRODUCTION

The rapid development of the current Internet and mobile communications industry has contributed to increasingly large-scale, heterogeneous, dynamic, and systematically complex networks. By evolving network technologies as well as increasing demands of modern applications, "general-purpose" protocol stacks are not always adequate and need to be replaced by application tailored protocols. To cope with the emergence of various device characteristics and application requirements, complex and custom design of high performance networking protocols is needed. Current methods for protocol design are mainly human-based and thus are burdened with various limitations. Firstly, design of new protocols is time-consuming and requires a specialized knowledge that is not trivial to acquire. Furthermore, once a protocol is designed, it lacks adaptability and flexibility to changes in the environment, since contemporary communication scenarios display dynamic and non-stationary properties. In addition, changes in network are so fast and frequent that no human-based mechanisms can follow them accurately. Finally, current approaches are limited to human perception and understanding of this field, thus limiting the potential for extracting new and unexpected insights during the protocol design process. In such traditional protocol design process in which there is no intelligence, a static predefined set of rules is hard-coded for each host to follow. These rules are usually defined by if-then-else statements or are embedded a state-event table. When a particular event is triggered, a host executes the corresponding action. The actions thus cannot be changed "on the fly" with respect to the continually changing environment[17]. Moreover, when designing a protocol, designers consider prior assumptions about the network, which are not quite realistic for today's complicated, dynamic networks where topology, resource, and node mobility are subject to unpredictable change.Therefore, replacing this inefficient human-based protocol design process by a novel paradigm that enables rapid design of efficient, flexible, and high performance protocols that intelligently adapt to different application requirements, user objectives, and network conditions is highly desired.

In the last decade Machine Learning (ML) has been widely used in network domain. By having the ability to interact with complicated environments and decision making, ML techniques provide promising solutions for higher network performance [16]. These techniques include supervised learning (SL), unsupervised learning (USL), and Reinforcement Learning (RL) which are used in many network sub-fields including resource allocation, parameter optimization, traffic prediction and classification, as well as specialized domains of communication protocols(e.g., congestion control,routing ,Medium Access Control (MAC) in wireless and wireless sensor networks (WSN) , etc.,). RL is a model-free ML technique that is suitable for unknown environments where decision-making ability is crucial.In RL, the agent continuously updates its policy, which maps observed states to choices of actions, such that the objective function is maximized. RL represents the desired performance metric and optimize it as a whole. For example, rather than tackling every single factor that affects network performance such as the wireless channel condition and node mobility, RL monitors the reward resulting from its actions. This reward may be throughput, which covers a wide range of factors that can affect the performance. In addition, RL does not build explicit models of the other agents' strategies or preferences on action selection [17]. Recently, RL and Deep Reinforcement Learning (DRL [1]) which integrates deep neural networks and RL, are used as efficient solutions for Dynamic Spectrum Access(DSA) [3, 19], designing MAC protocols [10], [13], [12], [11] and congestion control algorithms [6]. We propose a novel RL-based framework for communication protocol design.

2 RELATED WORK

Current trend on the problem of emerging MAC protocols with machine learning focuses mainly on new medium-access policies. The research mostly focused on contentioned-based policies [15], [14], Dynamic Channel Access (DSA) such as [2, 5, 8].

Reinforcement Learning (RL) is widely used for designing MAC protocols in WSNs and wireless networks. In the following we describe the prior works that exploit RL to enhance MAC protocols. S-MAC [18] applies RL to adaptively tune the duty cycle. In S-MAC, nodes form a virtual cluster in order to provide a common schedule between neighboring nodes, and a small SYNC packet is exchanged between the neighbors to ensure synchronized waking period to reduce control overhead. RL-MAC [7] is another adaptive MAC protocol that has been designed for WSNs. Each node using RL-mac not only considers its own local state but also infer the state of other neighboring nodes in order to achieve near optimal MAC policy. The local observation of the node includes successful transmission and reception of packets during the active cycle, while the neighboring observation infers the failed transmissions to inform the receiver about the missed packets. ALOHA-Q [4] the technique combines the slotted ALOHA and Q-Leaning. In this design, each node has a fixed frame structure that contains multiple time slots. Packets are transmitted during these time-slots and each node stores a Q-value for individual time slots within a frame. Therefore, slots with the higher Q-value are more favorable for the next transmission by the node. Consequently, each node is assigned with a unique time slot for transmission. Self-Learning Scheduling [9] approach is designed to minimize the energy consumption and maximize the throughput. In this approach, nodes share the same duty cycle and waking up time. In each duty cycle, a node can be either in sleep, idle, or active state. The Q-values are updated based on the energy costs and packet queue length . The recent works [10], [13], [12], [11] focus on random access MAC protocol design in 802.11 LANs by selecting appropriate protocol blocks. The authors propose a novel approach to decouple a protocol into its functionalities. The RL agent then selects propoer set of blocks based on the signal it receives from the network environment.

3 IMPLEMENTATION AND EVALUATION

3.1 Implementation

We use RL to design an agent that is able to learned optimized mac protocol uplink and downlink in a network where nodes communicate with an Access Point(AP).

We calculate reward as a function of maximum number of time steps in an episode. Table 1 shows the R performance in terms of # of uplink devices. performance is evaluated in an environment with 5 devices. The environment was configured with P = 1, number of episodes = 32 and an empty buffer. Agent was trained with a learning rate of 0.08.

Table 1: Methods and Technologies that brings video analytics at Edge

# of Uplink Devices	R Performance
1	-5
2	-10
3	-25
4	-31
5	-35

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