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Multi-Agent Deep Reinforcement Learning for Collaborative Computation Offloading in Mobile Edge-Computing

Abstract

In this work, we study collaborative computation offloading in mobile edge computing (MEC) to support computation-intensive applications. Mobile devices (MDs) can offload their computation to edge nodes (ENs), where we leverage edge-to-edge offloading to further enhance the MEC's computing capabilities. This however presents significant challenges due to the need for real-time and decentralized decision-making in the highly dynamic MEC environment especially with collaborative offloading. We design a queue-based multi-layer model scenario and formulate the joint offloading problem as a decentralized partially observable markov decision process (Dec-POMDP), where each MD and EN constructs and trains offloading agents to achieve high performance and efficient resource utilization in MEC. To solve the formulated problem, we propose a multi-agent deep reinforcement learning (DRL)-based approach, where multiple agents collaborate to make distributed decisions in an uncertain MEC environment through global optimization.

Terms— Mobile edge computing, Computation offloading, Decentralized partially observable markov decision processes (Des-POMDP), Multi-agent deep reinforcement learning

1 Introduction

To meet the rapidly growing demands of computation-intensive and time-sensitive AI applications [1], mobile edge computing (MEC) [2] is emarged as a promissing solution, by allowing mobile devices (MDs) to offload computational tasks to edge computing nodes (ENs) located near to them. However, MEC often suffers from their dynamic and uncertain environment, such as time-varying conditions, heterogeneous devices, and frequent communication requests. Reinforcement learning (RL) [3] has been widely proposed as an effective tool that enables MEC network entities to interact with the environment for learning an optimal policy, usually modeled as a markov decision process (MDP) [4].

In an MEC-enabled network, a key challenge is determining whether and how to offload each task, as well as selecting the appropriate computing entities and transmission links for computation offloading. This problem has been widely investigated in recent RL-based research, where tasks from MDs are offloaded to ENs through device-to-edge (D2E) transmission links. For example, Zhao *et al.* in [5] developed a computation offloading algorithm to address competition for wireless channels. To handle deadline-constrained computational tasks, Tang *et al.* in [6] introduced a distributed offloading algorithm that manages uncertain workload dynamics at the edge nodes. Zhou *et al.* in [7] investigated the joint optimization of computation offloading and resource allocation to minimize energy consumption across the entire MEC. Liao *et al.* in [8] introduced a Deep RL (DRL)-based algorithm for performing online computation offloading in MEC. This algorithm optimizes transmission power and CPU frequency when minimizing both task computation delay and energy consumption. Sun *et al.* in [9] tackled both computation offloading and service caching problems, proposing a hierarchical DRL framework to minimize long-term average service delay. We also in [10] studied the computation offloading problem under strict task processing deadlines and energy constraints, proposing a distributed algorithm to maximize each user's long-term QoE individually. However, research [5]–[10] primarily overlooked the potential for collaboration among ENs, specifically failing to leverage underutilized computing resources that could be shared among multiple ENs to enhance network efficiency. To achieve optimal utilization and high performance in MEC environments, it is worth exploring a collabrative offloading framework, where both MD and EN can offload computation-intensive tasks to a particular EN through D2E and edge-to-edge (E2E) transmission links, respectively, according to their computation and communication capacities.

The problem are challenging due to the online and asynchronous decision-making requirement for each task, while multiple different decision-makers collaborate to asynchronous offloading decision-making. Specifically, each MD and EN should act as different agents to make offloading decisions based on their partial observation of the global network state, which makes single-agent RL methods inefficient and sometimes inapplicable. Single-agent RL learns its decision-making policy independently and treats other agents as part of the environment, which may cause the non-stationarity issue [11] and significantly reduce learning efficiency and network performance. To tackle with the non-stationarity issue in MEC environments, RL-based studies have turned to the use of multi-agent RL (MARL)-based methods (e.g., [12], [13], [14], and [15]), where multiple agents collaborate to make distributed decisions through global optimization.

2 Problem Statement and Solution Approach

In this work we are interested in exploring a collaborative offloading framework, while effectively address multi-agent systems challenges. We formulated the collaborative offloading problems for both MDs and ENs as a decentralized partially observable markov decision process (Dec-POMDP) [16], where different decision-makers interact with each other based on partial observations and limited information about the network and other entities to achieve overall system performance. To solve the problem, we propose a multi-agent DRL-based framework, where each MD and EN constructs and trains its own agent to make different layers' decisions. The key idea of this collaborative framework is to decouple task offloading decisions by making decisions at different layers at different time points. This approach allows each layer's decision-making processing to dynamically adjust based on the current network state and resource availability, thereby improving the overall efficiency and responsiveness of the system. Specifically, we design a multi-agent deep deterministic policy gradient (DDPG) [17] algorithm, where each agent has a decentralized actor and a centralized critic and can be applied to collaboration in multi-agent settings. Overall, this work aims to provide a novel collabrative framework for computation offloading problem in MEC, addressing the challenges of online decision-making and multi-agent environments. In summary, the key contributions of this work are summarized as follows.

1. **Novel Collabrative Model Scenario:** We consider a novel queue-based collaborative computation offloading framework in an MEC-enabled network, which incorporates both D2E and E2E offloading mechanism, and can significantly enhance the offloading performance.

2. **Novel MARL-Based Solution:** We focus on computation offloading problem, aiming to tackle the online and asynchronous decision-making challenge in multi-agent environments. We propose MARL-based algorithms, which enable MDs and edge ENs to collaboratively make distributed decisions through global optimization.

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