

Mobile Edge Computing and Artificial Intelligence: A Mutually-Beneficial Relationship

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Abstract

This article provides an overview of mobile edge computing (MEC) and artificial intelligence (AI) and discusses the mutually-beneficial relationship between them. AI provides revolutionary solutions in nearly every important aspect of the MEC offloading process, such as resource management and scheduling. On the other hand, MEC servers are utilized to avail a distributed and parallelized learning framework, namely mobile edge learning.

1. Introduction

Computing is increasingly ubiquitous in all aspects of our life, which adds additional functions to phones, tablets, and wearable devices. Computing requirements for mobile applications are increasing rapidly to meet the need for computational-extensive applications of mobile users, such as virtual reality and real-time online gaming. Mobile edge computing (MEC) is a promising solution to avail adequate computing and storage capabilities in close proximity to mobile users [1]. The main target of previous generations wireless networks was to provide adequate wireless speeds to make the transition from voice-centric to multimedia-centric viable. The mission of 5G networks is quite different and much more complex, namely to uphold communications, computing, control and content delivery.

In 5G wireless networks, ultra-dense edge devices, such as wireless access points and small-cell base stations are deployed, each providing computation and storage capabilities at the network edge. Moreover, unmanned aerial vehicles have attracted significant attention to provide aerial-ground cooperative MEC frameworks due to their agile management, flexible deployment, and low cost [2].

Considering such diverse resource availability and the massive amount of devices and data generated by the computationally intensive applications, there is a need for powerful tools and techniques capable of allocating both communications and computing resources to users. Artificial intelligence (AI) solutions, in particular deep learning networks, represent a fit to address the hurdle and empower intelligent resource management for efficient MEC in real-time and dynamic scenarios.

Recently, the concept of mobile edge learning (MEL) has been defined, in which MEC interplays with AI in the sense that the learning model, parameters, and data are distributed across multiple edge servers, and an AI model is trained from distributed data [3]. Such a distributed learning model is known as federated learning, in which a node plays the role of the orchestrator that aggregates locally derived parameters and returns globally updated parameters to the servers

(learners) [4]. Such a mutually benefiting interaction between MEC and AI paves the way for an intelligent-pipe, in which the communication network becomes intelligent and self-driven.

2. Mobile Edge Computing

The first real-world MEC platform—introduced by Nokia Networks and Intel—aims to support the base station with computation capability to providing intelligent services and collecting real-time network data such as subscriber locations and cell congestion [1]. Saguna and Intel introduced a fully virtualized software-based MEC platform, which can provide an open environment for running third-party MEC applications [5]. The European Telecommunications Standards Institute formed proofs-of-concepts to demonstrate the viability of MEC implementations as a key technology of the 5G era [6].

To be a viable and competitive option, the offloading process in a MEC framework should be implemented with low energy consumption, low offloading error, and low latency. A large body of literature has studied different offloading policies to address these requirements, such as: *binary* offloading, in which the mobile device determines whether a task should be offloaded to the MEC servers or computed locally; and *partial* offloading, in which a portion of the computation is performed locally at the mobile device and the other portion is offloaded to the MEC servers. More evolved policies have also been studied, in which the task of a mobile device is partially processed at cloud servers and partially offloaded to the edge servers for computing. Both parallel and sequential offloading schemes have been addressed in the literature [7].

The massive amount of edge devices and great variety of applications and services make resource management in the MEC framework a complex process. Even in the simple scenarios of offloading single user's tasks or offloading to a single server, the offloading decision problem is NP-hard or NP-complete [8]. Moreover, the following practical issues need to be addressed in the computational task offloading process:

- *Prioritized tasks*: In practical scenarios, some tasks (or users) require higher priority to access the computation resources;
- *Dependency among tasks*: In many applications, the computation of a task depends on the computed results of other tasks. Inter-tasks dependency cannot be ignored and has a significant effect on the offloading and computation procedure;
- *Repeated tasks*: More than one user may offload the same task, and such a duplicated effort reduces the effectiveness of the offloading process. Collaborative offloading schemes could reduce the offloading cost and improve the offloading process.

With such requirements and potentially large number of variables, MEC offloading ends up being a high complexity and dimensionality problem, which requires powerful and real-time resource management algorithms with ability to respond to changes in the offloading environment.

3. Artificial Intelligence Approaches for MEC

AI can be viewed as a collection of algorithms that empower intelligent machines to improve their performance on descriptive, predictive, and prescriptive models. Conventional AI approaches may be good enough for handling moderate-dimensional situations; however, the MEC resource management problem requires dynamic solutions and ability of dealing with high dimensionality scenarios efficiently. For example, reinforcement learning has shown promising results for resource management, such as abstract computing or memory resources [9] and production scheduling and control [10]. First, the resource management and scheduling problem is modeled as a Markov decision process. Then, a reinforcement technique is used in which an agent finds optimal actions in order to optimize the performance by maximizing the reward of each action. The agent trains a deep neural network—an artificial neural network with multiple layers between the input and output layers—by performing an iterative state transition process and characterizing each state with main features. The iterations continue until the agent decides to use the best action found so far.

Let us consider the scenario in which the best offloading decision needs to be found, which associates each task generated by mobile users with one of the available MEC servers, with the goal of minimizing the offloading error, latency, energy consumption, or a combination of these objectives. In this case, the state of a server can be described by its resources such as computing speed and communication channel quality. User requirements include tasks payload size and the required processing cycles; dependency and/or priority among the tasks/sub-tasks also needs to be taken into account. Then, an agent iteratively associates the users' tasks with servers and records the resulting reward, which is the reduction of the objective. The features describing the status of the server and the requirements of users are fed to learn the deep neural network. The generalization capabilities of the deep neural network yield general scheduling policies which are not just tuned to the states encountered during training, but are adaptive to be applied to unknown states, too. Figure 1 illustrates the basic components of an agent.

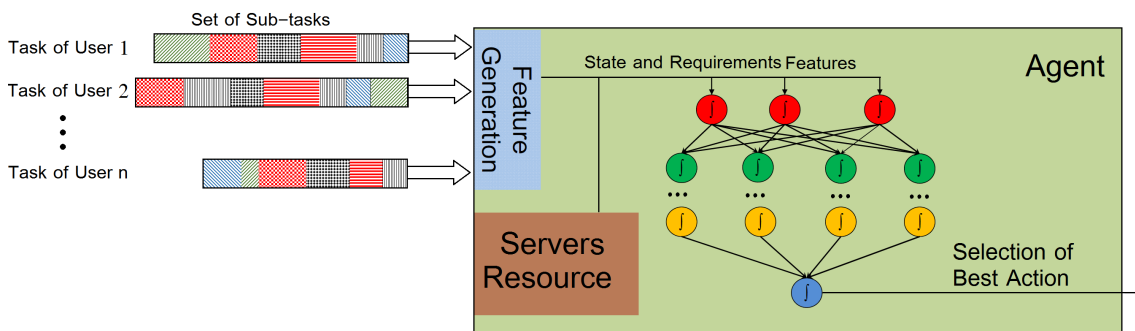


Figure 1. An agent in which the inputs of the deep learning network are features describing the servers' current status and users' requirements.

For a multi-agent scenario, multiple interacting intelligent agents collaborate to reinforce the learning process that results in a lower objective. The critical part in designing a reinforcement learning algorithm is to define a reward function that captures the offloading requirements and governs the algorithm performance.

4. From Edge Computing to Edge Learning

In many realistic applications, an AI algorithm is a computationally-expensive task and requires large-scale training samples. The convergence rate of the learning process can be improved using the federated learning technique in which the learning process and the training samples are parallelized between processing nodes (a.k.a., learners). The massive deployment of servers at the network edge motivates the concept of MEL, in which the computationally-expensive AI algorithm is distributed and executed on the edge servers [4]. In the MEL framework, each server (learner) performs training iterations to train its local learning model using local training samples. Once each learner finishes its iterations, it forwards the resulting features to the orchestrator. The orchestrator—which is a logical component that can run on a remote cloud, network element, or edge node—then aggregates the local features and updates all learners. MEL enables the AI algorithm gain diversity from the vast range of data located at different servers. It is worth mentioning that the learners and orchestrator exchange the extracted features, whereas the raw training data remain on the learners. The extracted features are small in size in comparison with the raw training data; consequently, transmitting the extracted features reduces the burden on the communication channels. Figure 2 illustrates the general MEL model.

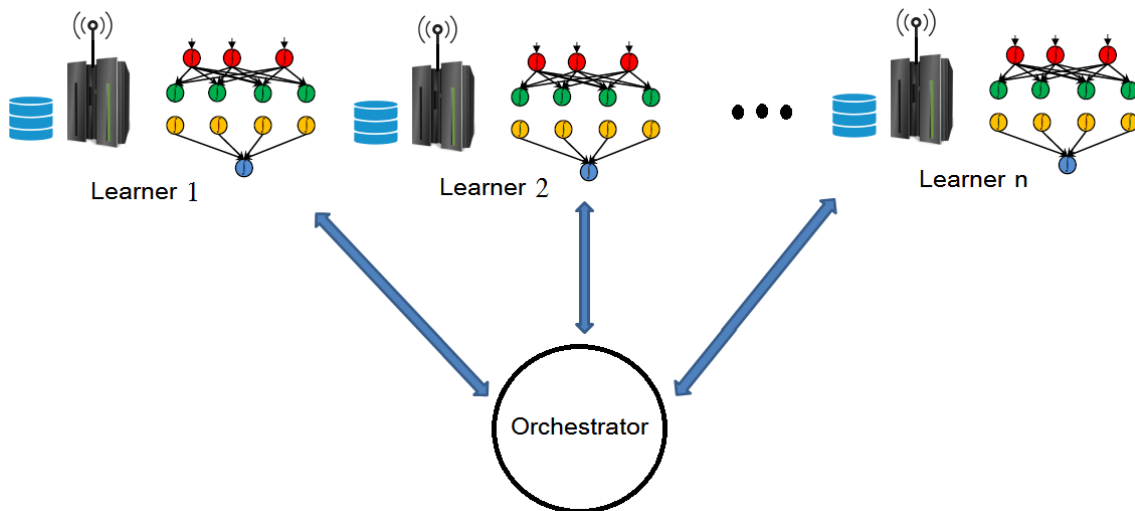


Figure 2. MEL model.

It is envisioned that beyond 5G wireless networks will be required to support ubiquitous AI services from the core to the end devices of the network. AI will play a critical role in designing and optimizing beyond 5G wireless networks architectures, protocols, and operations. Meanwhile, the design of the beyond 5G wireless networks architecture will follow an “AI native” approach, where intelligentization will allow the network to be smart, agile, and able to learn and adapt itself according to the changing network dynamics [11].

5. Conclusion

This article has briefly presented the basic concepts, benefits, and integration of MEC and AI. The potential of incorporating extended AI functionalities in MEC has been discussed. The idea of MEL has been introduced, in which MEC servers are utilized to distribute and parallelize the resource-intensive learning process of an AI model. It is envisioned that AI at the edge will be an integral part of beyond 5G wireless networks.

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