Towards Self-learning Edge Intelligence in 6G

Yong Xiao, Guangming Shi, Yingyu Li, Walid Saad, and H. Vincent Poor

***Abstract*—Edge intelligence, also called edge-native artificial intelligence (AI), is an emerging technological framework focusing on seamless integration of AI, communication networks, and mobile edge computing. It has been considered to be one of the key missing components in the existing 5G network and is widely recognized to be one of the most sought-after functions for tomorrow's wireless 6G cellular systems. In this article, we identify the key requirements and challenges of edge-native AI in 6G. A self-learning architecture based on self-supervised Generative Adversarial Nets (GANs) is introduced to demonstrate the potential performance improvement that can be achieved by automatic data learning and synthesizing at the edge of the network. We evaluate the performance of our proposed self-learning architecture in a university campus shuttle system connected via a 5G network. Our result shows that the proposed architecture has the potential to identify and classify unknown services that emerge in edge computing networks. Future trends and key research problems for self-learning-enabled 6G edge intelligence are also discussed.**

***Index Terms*—6G, Edge Intelligence, Artificial Intelligence, Self-learning, Self-supervised Learning.**

I. Introduction

The wireless networking landscape is witnessing an unprecedented evolution that has led to the deployment of the fifth generation (5G), the latest iteration of mobile technology that promises to support a plethora of innovative services including the Internet-of-Things (IoT), autonomous vehicles, Augmented Reality/Virtual Reality (AR/VR), among others. Simultaneously, a broad range of research is being initiated to look into the sixth generation (6G) of wireless cellular systems [1] whose primary goals include not only a much improved data transportation network but also a highly intelligent and fully autonomous human-oriented system. In particular, 6G will revolve around a new vision of *ubiquitous AI*, a hyper-flexible architecture that brings human-like intelligence into every aspect of networking systems.

There are already initiatives to promote the applications of AI in 5G. In particular, ITU-T has established the focus group (FG) on 'machine learning for future networks including 5G' (ML5G) [2] to promote unified architectural development and interface design for the cost-effective integration of machine learning (ML) into 5G and future networks. 3GPP is also reported to work on new AI-inspired functional modules to monitor and improve the performance of the service-based architecture (SBA).

Despite its great potential, we have yet to observe a wide spread deployment of AI in wireless systems due to the following three major challenges:

(1) **Limited Resources:** The storage space and computational resources needed for executing AI algorithms often exceed those of existing wireless systems.
(2) **Lack of High-quality Labeled Data:** Most existing AI algorithms require a large number of (high-quality) labeled data for learning and model training. Meanwhile, the massive volume of data generated by wireless networks is mostly unlabeled raw data. Manually labeling these datasets is time-consuming and, in most cases, impractical. This challenge is further exacerbated by the fact that wireless network data is highly random in nature and the required quantity and quality of the labeled data for model training and construction are closely related to a range of uncontrollable and unpredictable factors such as geographic locations, operating frequency, distribution of network infrastructure, user mobility, software and hardware configurations, and others.
(3) **Lack of AI Optimized Architecture:** The existing wireless network architecture has not been originally designed with AI-inspired applications and services in mind. Deploying resource-consuming AI solutions may strain the capacity of the wireless infrastructure, which has already been overloaded with resource-hungry applications. Currently, there is still a lack of an AI-native networking architecture that can strike a balance between the resource need for delivering AI functions and that for supporting the fast-growing number of mobile applications with stringent requirements.

One possible solution to address the above challenges, is *edge intelligence*, also referred to as edge-native AI [3], [4], a novel technological framework focusing on seamless integration of AI, communication networks, and mobile edge computing[1]. In particular, by deploying a massive scale of decentralized mobile edge servers to perform AI-based processing and decision making closer to where the data and service requests are generated, edge intelligence lays the foundation for ubiquitous and accelerated AI integration in the next generation wireless system.

Edge intelligence is commonly considered to be one of the key missing components in 5G [5] and is well recognized as a major enabler for 6G to unleash the full potential of network intelligentization [6], [7]. The role of AI-enabled applications

Y. Xiao and Yingyu Li (corresponding author) are with the School of Electronic Information and Communications at the Huazhong University of Science and Technology, Wuhan, China 430074 (e-mail: {yongxiao, liyingyu}@hust.edu.cn).

G. Shi is with the School of Artificial Intelligence, the Xidian University, Xi'an, Shaanxi 710071, China (e-mail: gmshi@xidian.edu.cn),

W. Saad is with the Department of Electrical and Computer Engineering at Virginia Tech, Blacksburg, VA 24061 (e-mail: walids@vt.edu).

H. V. Poor is with the School of Engineering and Applied Science, Princeton University, Princeton, NJ 08544 (e-mail: poor@princeton.edu).

[1]There are other concepts such as fog computing and multi-access edge computing that convey a similar meaning. In this article, we use these terms interchangeably to mean any capable devices other than cloud data centers.

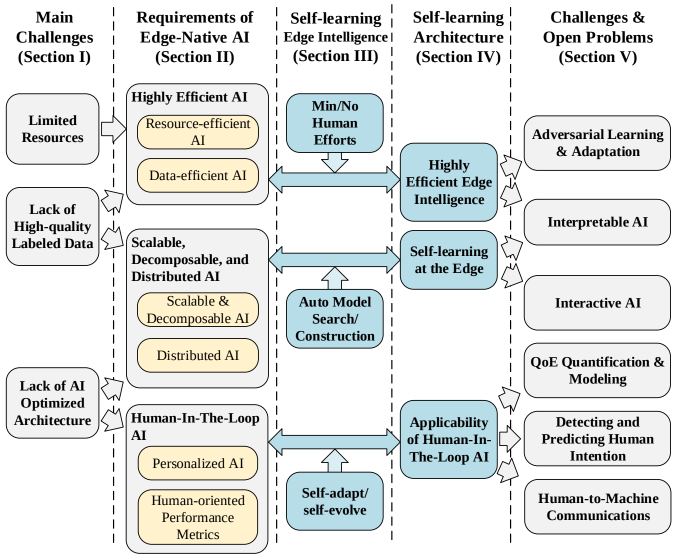

Fig. 1. Key requirements, potential self-learning-based solutions, and future challenges of edge-native AI.

in terms of architecture, functional components, requirements, and applications in 6G [8] compared with those in 4G and 5G are summarized in Table I.

It is expected that 6G networking systems will be in a massive scale supporting over 125 billion of connected devices by 2030. It is therefore critically important to develop an automatic data collecting, labeling, and processing architectural framework that allows the edge computing network to adapt and evolve by itself. Self-learning is a emerging area in ML that allows agents to sense, learn, reason, decide, adapt, and evolve by themselves without any hand-labeling efforts nor human involvement [9]–[11]. It leverages recent advances from a range of AI approaches including self-supervised learning [12], self-taught learning [10], auto-ML [11], etc., so as to achieve automatic label generation, feature extraction, representation learning, and model construction. It has achieved promising results under some specific use scenarios and has been considered as one of the most important future research directions of AI [11].

The main contribution of this paper is to identify key requirements and trends that will drive edge intelligence for 6G, especially from the perspective of self-learning. In particular, we propose a self-learning-based architecture and discuss its potential in addressing some of the key challenges in 6G. To the best of our knowledge, this is the first work that surveys self-learning and its possible applications in 6G. We summarize the main structure of this article including the key requirements, potential self-learning-based solutions, and future challenges to be discussed in the rest of this article in Fig. 1.

II. Requirements for Edge-native AI

The substantial impact of 6G in terms of data collection, transportation, processing, learning, and service delivery will shape the evolution of network intelligentization, catalyzing the maturity of edge intelligence. In particular, next-generation edge-native AI technologies must be able to meet the following requirements raised by 6G.

A. Highly Efficient AI

1) Resource-efficient AI: Traditional wireless networks mainly focus on maximizing the data transportation capability of wireless resource such as spectrum and networking infrastructure. However, with more computationally-intensive and data-driven AI tasks being adopted by 6G, the extra-resources required to perform AI-based process, including data coordination, model training, computing, caching, etc., must be carefully evaluated, quantified, and optimized. Although there are already some communication-efficient AI algorithms such as deep reinforcement learning, transfer learning, and federated learning that exhibit reduced communication overhead, these algorithms may still require considerable amount of resources compared to most data-centric applications [13]. Also, these algorithms can only be applied to some very specific learning tasks.

2) Data-efficient AI: As mentioned earlier, compared to computer vision systems, it is often more difficult to collect sufficient amounts of high-quality labeled dataset under each possible wireless environment and networking setup. Therefore, it is of critical importance to design data-efficient self-learning approaches that only require a limited or no hand-labeled data as input. There are already some data-efficient AI algorithms being introduced recently. For example, the self-supervised approach combines the advantages of both supervised and unsupervised AI approaches by automatically creating labels from the raw dataset for some pretext tasks and use that to learn the representations in a supervised fashion. Unfortunately, these approaches are still in their infant stage and can only be applied in a number of very limited tasks.

B. Scalable, Decomposable, and Distributed AI

1) Scalable and Decomposable AI: In contrast to a high-performance cloud data center, which is typically built based on the centralized architecture with a unified interface supported by compatible software and hardware components, edge computing is a highly distributed architecture, consisting of a large number of edge servers with heterogeneous processing and caching capabilities as well as energy and size constraints. Edge servers may also be deployed and managed by multiple service providers, supporting different software (Android, Ubuntu, or Windows) and hardware (ARM, RISC, or X86) platforms. It is therefore important to provide a scalable and decomposable data and task processing framework to allow parallel processing of tasks that span the cloud as well as multiple edge servers. One possible solution is to extend the network softwarization approach to edge hardware and software platforms. In this way, heterogenous hardware and software platforms can be abstracted into a set of virtual functions that execute different AI tasks.

2) Distributed AI: One of the key challenges for edge intelligence is to design a simple, scalable, and distributed AI approach that supports a large number of distributed edge servers as well as cloud data centers to jointly perform the

TABLE I
ROLES OF AI IN 4G, 5G, AND 6G

	Cloud-based AI (4G)	AI-enhance Functions (5G)	Edge-native AI (6G)
Architecture	Communication-oriented architecture	Service-based architecture (SBA)	AI-native edge intelligence
Functional Components	Over-the-top AI applications deployed in cloud data center delivered via 4G networks	Preset functional modUales to monitor and enhance performance of SBA	Seamlessly integration of AI, communication network, and edge computing
Key Requirements	Mostly applied in non-safety-related applications	Stringent latency and reliability requirements in some use scenarios, e.g., URLLC	QoE guarantee with self-adaptation & self-learning capability
Applications	Voice and image-recognition-based virtual assistant app	Self-driving vehicles, smart factory, AR/VR	Self-evolving smart city, interactive holographic communication, highly intelligent humanoid robot

same set of computational tasks. Distributed AI has attracted significant interest due to the recent popularity of federated learning and its extension-based solutions. However, both distributed AI and federated learning are still in their infancy. It is expected that the federated learning-enabled architecture will play an important role in the future evolution of distributed AI-based 6G services and applications.

C. Human-In-The-Loop AI

1) Personalized AI: Personalized AI will play a key role in 6G to improve the decision making of AI algorithms and help machines understand better about human users preferences and make more human-preferred decisions [12]. There are two types of Human-In-The-Loop AI approaches. The first one is to include human intelligence as part of the decision-making process. For example, an AI algorithm can leverage human intelligence to make decisions when the machine itself cannot make correct decisions or the cost of making the incorrect decision is high, e.g., in self-driving vehicular systems, each vehicle can turn the control back to human drivers when it faces unknown situations or cannot make a safety-guaranteed driving decision. The other approach is to allow agents to observe their past interactions with human users and learn to improve the decision-making process.

2) Human-oriented Performance Metrics: Instead of simply focusing on maximizing traditional performance metrics, such as throughput, network capacity, and convergence rate, the performance of 6G and AI must be jointly measured and evaluated by taking into consideration characteristics and potential responses of users. In addition, with 6G and mobile services becoming increasingly indispensable to human society, it is also important to develop novel metrics that can help evaluate the social and economic dimensions of 6G and AI convergence.

III. SELF-LEARNING EDGE INTELLIGENCE

Self-learning edge intelligence has the potential to significantly reduce the human efforts involved in data processing and model development by enabling self-detection and adaptation over unknown events, and most importantly, automatic model construction, learning, and evolving according to the changes of data features and environments. Self-learning edge intelligence in 6G must meet the following requirements.

A. Minimized/No Human Effort

The success of edge intelligence is expected to heavily rely on self-learning AI mechanisms with minimal human efforts for manual data processing and labeling. One promising solution is to leverage recent advances in self-supervised learning to enable model training based on automatically generated pseudo-labeled data, e.g., using self-supervised learning and generative neural networks such as generative adversarial networks (GANs) and variational autoencoders (VAEs). In the next section, we will introduce a self-supervised GAN-based architecture and present a case study to demonstrate the potential of automatic pseudo-labeling and data synthesizing in unknown service identification and classification.

B. Automatic Model Search and Construction

It is known that each individual ML model or algorithm possesses a specific structure and often comes with a set of sophisticated human expert-designed strategies or empirical rules for model construction and tuning. Recently, a new research direction, known as automatic ML (AutoML) has emerged. The goal of AutoML is to automate the architecture/model search across a range of existing ML approaches. It has attracted significant interest from both industry and academia. Developing simple and effective AutoML solutions will be essential for the practical implementation for self-learning edge intelligence networking systems.

C. Self-adaptation and Self-evolution

Most existing AI approaches assume the system environment to be stationary within a certain period of time, and thus, decisions can be made based on a fixed known model or policy trained on a given dataset. For example, supervised learning, one of the mature and better-understood AI approaches, needs to be trained with properly-labeled data with pre-knowledge of all possible patterns. These approaches cannot work in continuously changing environments. Online learning and reinforcement learning-based approaches whose goal is to maximize the long-term reward have a strong potential to overcome the above challenges. For example, deep reinforcement learning has already been successfully adopted in Google's AlphaGo to beat the world's best human player in the game of Go. In addition to self-adapting to various known scenarios, self-learning edge intelligence should also have the capability to learn and self-evolve in unknown environments. Data synthesis is expected to play a major role in identifying and classifying various emerging unknown situations from a limited number of real-world data. As will be shown in the next section, compared to the traditional clustering solutions, novel data synthesizing solutions can significantly improve the

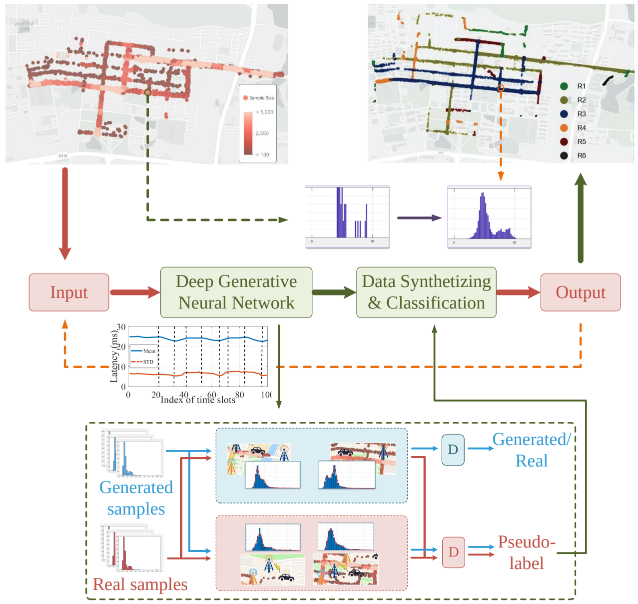

Fig. 2. The proposed self-learning architecture.

Fig. 3. A connected vehicular system for evaluating the performance of our proposed self-learning architecture.

accuracy and learning speed on recognizing and classifying unknown services.

IV. A Self-learning Architecture for Edge Intelligence

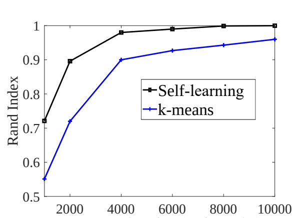

Fig. 4. Classification performance of the proposed architecture.

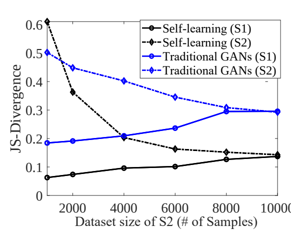

Fig. 5. JS-divergence between the synthetic data and real data for both services S1 and S2 under different dataset sizes of service S2.

The success of 6G will heavily rely on a simple and effective edge intelligence solution to meet all the above requirements and can, at the same time, self-adapt and self-evolve according to the future dynamics of the system. In this section, we introduce a simple self-learning architecture to demonstrate the potential improvement that can be achieved in unknown service traffic classification and prediction throughout a large-scale edge intelligence system. We use the connected vehicular network as a case study to evaluate the performance our proposed architecture under some specific scenarios. Finally, we discuss some possible extensions that can be brought by our self-learning architecture to meet some of the requirements of edge-native AI discussed in Section II.

A. A Self-learning Architecture

In this section, we propose a self-learning architecture based on self-supervised GAN with multiple generators [12] with the goal of automatically learning features and constructing ML models to identify and classify emerging unknown services from raw crowdsourcing data distributed across a wide geographical area as illustrated in Fig. 2. Our proposed architecture exploits the generative learning feature of the GANs approach in which multiple generators are trained to produce synthetic data that can capture the mixture of distribution of traffic data generated from multiple services across various locations in the coverage area. By introducing a classifier to maximize the distribution difference (e.g., measured by Kullback-Leibler (KL) Divergence) of synthetic data produced by different generators, we can prove that it is possible to train each generator to produce synthetic data samples that follow the same distribution as the real traffic data associated with each individual service. We can then leverage the self-supervised learning approach to automatically create pseudo-labels for the synthetic data produced by each generator. These created pseudo-labels will then be exploited to train a deep neural network model to identify and classify various service data across different locations throughout the service region [14].

Different from the traditional GANs, the discriminators in the proposed architecture will perform two tasks at the same time: (i) recognizing whether the data is real or fake, and (ii) identifying which generator the data is associated with. The generator is unaware of these tasks but will learn to produce synthetic data samples with similar characteristics to the real recorded data. Both generator and discriminator try to optimize different and opposing objective functions until an Equilibrium solution is reached.

To reduce the computational load of each edge server, the generators and discriminators of the proposed architecture can be deployed separately across multiple edge servers, each trains the model with a subset of data. Another potential solution to reduce the computational complexity for training our GANs-inspired architecture is to leverage transfer learning and exploit the preliminary knowledge and model learned by other users or network components, so as to further reduce the computational load in model training.

B. Case Study and Performance Evaluation

We consider the latency-sensitive connected vehicular system consisting of six campus shuttles connected to two edge servers as well as a cloud data center via a 5G network as a case study to evaluate the performance of our proposed architecture. We have developed a dedicated smart phone app [15] to monitor and keep track of the data delivery latency of 5G network connections between the moving shuttles and the associated edge servers as well as a cloud data center from a major service provider as shown in Fig. 3. In particular, we simulate two unknown connected vehicular services, labeled as S1 and S2, with different latency tolerances. Service S1 is the edge-based service that fully relies on the closest edge server to deliver the servers. Service S2 the edge/cloud-mixed service that equally divides its computational loads to be uploaded to the cloud and edge servers to perform computationally intensive services. We assume each vehicle can only observe the overall service latency data and cannot know whether the latency is caused by edge server or cloud data center. We apply our proposed self-learning architecture with one discriminator and two generators to classify the latency data associated with different services. We simulate the scenarios in which service S2 is an emerging service with different numbers of data samples being mixed with service S1.

To evaluate the service classification performance of our proposed architecture, in Fig. 4, we present the rand index (RI)of the clustering solutions of our architecture compared to the existing solutions such as k-means when the dataset sizes of service S2 vary. We can observe that the RI of our proposed architecture approaches 1 (probability of false clustering decision is close to zero) with only a limited number of service S2 data samples being available in the mixture of dataset consisting of both service traffics. To evaluate the quality of synthesized data samples generated by our architecture, we also compare the difference between the real data distribution and the distribution of synthesized data samples produced by our architecture measured by Jensen-Shannon (JS) divergence in Fig. 5. Our result shows that, by applying our proposed architecture, the distributions of synthesized data for both services approach those of the real service data. To summarize, our proposed architecture can classify unknown services from a complex mixture of service data without requiring any human labeled dataset.

C. Potential to Meet 6G Requirements

The above self-learning architecture has the potential to be extended into more general forms to meet the various requirements raised by 6G.

1) Highly-efficient Edge Intelligence: In the above architecture, the main objective of the deep generative neural network is to produce synthetic data to capture the attributes of real service data. In other words, it is unnecessary to collect a large number of high-quality manually-labeled data for each individual service across the entire coverage area. Also, since the synthetic data can be directly produced by the edge server, the data uploaded from the user as well as the total traffic transported throughout the network can be significantly reduced. Our preliminary result also shows that the computational complexity of each edge server to perform the self-supervised GAN algorithm is also limited as long as the dataset sizes and heterogeneity among edge servers is limited, e.g., when each edge server covers a smaller-sized area with a limited service demand.

2) Self-adaptation and self-evolution at the Edge: Datasets collected by different devices can vary significantly in terms of their statistical features due to their different service types, use scenarios, user preferences, etc. The self-learning architecture is able to produce synthetic data that captures the distribution of any type of raw data input and can be automatically adapted to the change of the data types as well as other feature dynamics. Also the applicable areas and achievable solutions of self-learning architecture can be further enriched by recent developments on the integration of other state-of-the-art AI solutions, such as federated learning, semi-supervised learning [9], reinforcement learning, transfer learning, and autoML.

3) Applicability of Human-In-The-Loop AI: The prior knowledge and service preference of human users can be exploited to further improve the efficiency of the above architecture. In particular, human knowledge or any prior information can be directly used to design more pretext tasks for the self-supervised learning approach to further improve the self-learning performance. Also, the architecture also allows agents or system components to interact with human users by self-adapting to the changes of the environment or networks caused by human usage.

V. Challenges and Open Research Topics

A. Adversarial Learning and Adaptation

AI-enabled 6G will be exposed to various novel attacks that aim to compromise the data training and decision making process. It is, therefore, important to develop effective self-adaptive methods to learn, detect, and defend against these attacks. Currently, there is no effective solution to protect against many data-related attacks, such as data evasion and poisoning attacks. One possible solution is to include the data affected by these attacked as the input and build a self-learning system that is resilient to various types of attacks. For example, if the impact of these attacks on model training and data processing can be carefully evaluated, network providers can leverage some existing approaches such as replay-with-simulating to efficiently eliminate the adverse effect caused by these attacks on the learned model.

B. Interpretable AI

Wireless systems need to be engineered with justifiable results and performance guarantees when being integrated with different network components and for different requirements. Unfortunately, most existing AI solutions, especially deep learning-based approaches, follow a black-box approach without any clear explanation about why and how the approach led to the given outcome. Developing explainable AI with interpretable and predictable outcomes is one of the key challenges for applying AI in 6G systems.

C. Quality-of-Experience (QoE) Quantification and Modeling

6G is expected to focus more on optimizing and improving users' QoE instead of the QoS. QoE is more closely related to the subjective experience of users. It not only depends on the hardware and software configuration and capacity, but can also be influenced by a wide range of human-related factors such as personal feelings, emotions, and past experiences. It is also affected by age, gender, personality of the users, as well as some environmental conditions such as service time, location, and physical environmental elements. There is still lacking a general and effective model formulation that can quantify the QoE of human users considering all the above elements and conditions.

D. Interactive AI

With the popularity of AI-enabled smart devices and network elements, interactions between networking elements and mobile devices are expected to be much more complicated than before. The service performance in this case will not only be affected by the hardware and software capacity of each device but also its level of intelligence, including the response mechanism and learning speed and capability of all interacting users as well as their past and current interactions.

E. Detecting and Predicting Human Intention

Due to the random nature of human beings, user traffic and demands exhibit temporal and spatial fluctuations. For example, an autonomously driven vehicle can frequently switch back and forth between manual mode (with human control) and self-driving mode, causing large fluctuations in driving-assistant-related data traffic. This will affect the stability and robustness of network systems, especially in densely deployed networks. Developing an AI-based solution that can detect and keep track of human intention as well as the driving mode of vehicles will help the network to be better prepared with improved reliability and robustness. It will also help the network to understand more the human users' real-time QoE and adjust the service performance accordingly.

F. Intelligent Human-to-Machine Communications

It is expected that 6G will be supporting a much wider range of novel interactive services and applications involving direct or indirect human-to-machine communications. A universal and human-oriented networking framework in which different components of networking systems can sense, communicate, and interact according to the real intentions of human users, irrespective of different interfaces, backgrounds, languages, and protocols, is expected to emerge in 6G era.

VI. Conclusion

This article provided an overview of a possible research roadmap for 6G edge intelligence, from the perspective of self-learning AI. Potential requirements and challenges of edge-native AI in 6G have been identified. Motivated by the major challenges for incorporating AI in wireless networks, that include resource limitation, lack of labeled data, and no AI-optimized architecture, we proposed a self-learning architecture that supports automatic data learning and synthesizing at the edge of the network. We evaluate the performance of our proposed self-learning architecture in a campus shuttle systems connected to edge servers via a 5G network. Our result suggests that our proposed architecture has the potential to further improve the data classification and synthesizing performance even for unknown services in the edge computing network under certain scenarios. The potential of self-learning AI to address some other novel challenging issues of 6G edge intelligence is also discussed. We hope this article will spark further interest and open new research directions into the evolution of self-learning and its applications towards edge intelligence in 6G.

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Yong Xiao (S'09-M'13-SM'15) is a professor in the School of Electronic Information and Communications at the Huazhong University of Science and Technology (HUST), Wuhan, China. He is also the associate group leader in the network intelligence group of IMT-2030 (6G promoting group). His research interests include machine learning, game theory, and their applications in cloud/fog/mobile edge computing, green communication systems, wireless networks, and Internet-of-Things (IoT).

Guangming Shi (SM'06) received the M.S. degree in computer control, and the Ph.D. degree in electronic information technology from Xidian University, Xian, China, in 1988, and 2002, respectively. His research interest includes artificial intelligence, semantic analysis, brain-inspired computing, and signal processing. He is a Professor with the School of Artificial Intelligence, Xidian University. He is the chair of IEEE CASS Xi'an Chapter, senior member of ACM and CCF, Fellow of Chinese Institute of Electronics, and Fellow of IET. He was awarded Cheung Kong scholar Chair Professor by the ministry of education in 2012. And he won the second prize of the National Natural Science Award in 2017.

Yingyu Li is a postdoc researcher in the School of Electronic Information and Communications at the Huazhong University of Science and Technology (HUST), Wuhan, China. Her research interests include IoT, networking data analysis.

Walid Saad (S'07-M'10-SM'15-F'19) is a Professor at the Department of Electrical and Computer Engineering at Virginia Tech. His research interests include wireless networks, machine learning, game theory, cybersecurity, unmanned aerial vehicles, and cyber-physical systems.

H. Vincent Poor (F'87) is the Michael Henry Strater University Professor of Electrical Engineering at Princeton University. His interests include information theory, machine learning and networks science, and their applications in wireless networks, energy systems, and related fields. Dr. Poor is a Member of the National Academy of Engineering and the National Academy of Sciences, and a Foreign Member of the Chinese Academy of Sciences and the Royal Society. He received the Marconi and Armstrong Awards of the IEEE Communications Society in 2007 and 2009, respectively, and the IEEE Alexander Graham Bell Medal in 2017.