GUEST EDITORIAL
SPECIAL ISSUE ON ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR NETWORKING AND COMMUNICATIONS

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INTRODUCTION

RESEARCH in large-scale networking systems has been shaped and will continue to be guided by specific char- acteristics of applications and the underlying platforms and infrastructures. On the one hand, applications are growing at an accelerated pace, which is fundamentally unpredictable in both breadth and depth. On the other hand, the underlying networking has been the focus of a huge transformation enabled by new models resulting from virtualization and cloud computing. This has led to a number of novel architectures supported by emerging technologies such as Software-Defined Networking (SDN), Network Function Virtualization (NFV), and more recently, edge cloud and fog networking, or network slicing [1], [2]. This evolution towards enhanced design oppor- tunities along with increasing complexity in networking and its applications has fueled the need for improved network automa- tion in agile infrastructures. At the same time, their complexity has dramatically increased. The networking dynamics have had the effect of making it even more important and chal- lenging to design scalable network measurement and analysis techniques and associated tools. Critical applications such as resource allocation, network monitoring, security enforcement, or dynamic network management require real-time mecha- nisms for online analysis as well as efficient techniques foroffline deep analysis of massive historical data.

Artificial Intelligence (AI) and Machine Learning (ML) approaches, well known from scientific disciplines such as computer vision, natural language processing and speech recognition, are nowadays wide spreading to numerous areas, and they have been recently re- gaining attraction in the net- working domain. AI and ML represent a different paradigm to tackle these challenges. Its data-driven nature facilitates to automatically learn the complexity of the communica- tions and networking environment and to dynamically adjust protocols without human interactions. AI/ML techniques for network management, operations & automation are meant to improve the way we address networking today, it may require specific designs. They have been made possible for networking researchers, mainly owing to three technological trends: first, the cost of system prototyping has been reduced to an affordable level to academia. A prolific pool of open- source frameworks and technologies has helped to reduce the development effort for a system prototype with a proper reference design to a minimum level. Moreover, the cost of launching a new application for public trial has been driven to the minimum with the emergence of cloud computing technologies. Second, the emerging big-data paradigm has ren- dered it relatively easier for researchers to gain easy access to large datasets, which used to be heavily guarded by companies and practitioners. Via an AI engine, one can quickly obtain real-time knowledge about the system and its stakeholders. Finally, the emergence of programmable system technologies, i.e., software-defined systems, has made it feasible to realign the system design and implementation in a hot "plug-and-play" manner. Examples of programmable systems include SDN, NFV, storage virtualization and computing.

These trends have drawn attention to interdisciplinary approaches from communication networks and AI/ML research communities. On the one hand, researchers in com- munication networks are tapping into ML and AI techniques to optimize network architecture, control and management, leading to more automation in network operations. Interested readers are referred to a comprehensive survey on machine learning for networking [3]. On the other hand, researchers in the AI community are working with networking researchers to develop new AL/ML frameworks, able to cater for running a broad range of applications at scale.

However, in the current stage, applying AI/ML to networked systems remains inadequately understood and investigated.

Most of the proposed solutions are problem specific, in-house and difficult to benchmark. Although machine learning and big data analytic techniques that are able to characterize, detect, locate and understand complex behaviors, promise to shed light on this huge amount of data, smart and scalable approaches must be conceived to make them generally applicable in networking and communication systems. Finally, the explosion in volume and heterogeneity of data generated across the entire wireless and network stack has opened the door to innovative solutions and out-of-the-box thinking which in turn promises to improve current communication systems and networks, as well as fostering innovative solutions in new network-centric domains.

This special issue aims at addressing the current directions of research and at presenting novel contributions in the field of AI/ML applied to communications and networking, including scalable analytical techniques and frameworks capable of collecting and analyzing both online and offline massive datasets. Furthermore, its goal is to address innovative design approaches and use cases related to the application of AI/ML in communications and networking, to discuss open issues related to the application of machine learning into networking system problems, and to share new ideas and techniques for big data analysis in communication systems.

I. SPECIAL ISSUE OVERVIEW

This special issue has welcomed high-quality original con- tributions addressing the important challenges and presenting novel research solutions in the development of AI/ML tech- niques and their applications to computer and communication networks. Survey papers that offer a perspective on related work and identify key challenges for future research have been considered as well.

The timeliness and interest in AI and ML are reflected by the huge number of submissions. 152 papers were submitted by 600+ authors from over 27 countries and 6 continents. Asia is highly represented and mainland China has been the country to respond with most submissions to the call (40% excluding

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Hong Kong). Interestingly, most papers (90%) originated from academia. Only 4 papers have been identified out of scope and thus early rejected. The review process involved 369 individual reviewers, and each one evaluated at least one paper. The submitted papers were thoroughly reviewed and, where needed, some selected authors were given the opportunity to update and revise their papers to address in detail the reviewers' concerns. All revised manuscripts were then shepherded by one or two Guest Editors and it was finally decided to accept only twenty papers for inclusion in this special issue (an acceptance ratio of 13%).

The time between the initial submission and the online publication of the revised papers in this special issue was about 7 months.

The selected papers in this special issue are exploring how AI and ML can be used to address various areas in the design and performance management of networks and systems. It includes the following non-exhaustive list of topics, falling into three sub-categories of fundamental frameworks, net- work analytics, network optimization and network automation.The topics covered include terminal identification, interference coordination, data collection, data analysis, data privacy, traf- fic estimation/prediction, MAC resource allocation, schedul- ing, resource management and allocation, anomaly detection, congestion control, quality of experience, energy efficiency in wireless systems, backhaul and backbone networks, and fog or cloud nodes. Many contributions are targeting future 5G networks and focusing on wireless networks and IoT, while a few are more focused on edge computing and multimedia networks.

While it is difficult to appropriately cluster the 20 papers into specific categories, we can distinguish various applicative trends in the proposals, even though most of them address several topics:

A. Descriptive AI. It relies on a set of historical data to yield, thanks to AI techniques, insightful informa- tion and possibly prepare the data for further analysis. Potential areas include data collection and analysis, and related issues.

B. Predictive AI. It attempts to understand the causes of events and behaviors. Potential areas include fault diagnostics and anomaly detection, while provid- ing insight on performance and Key Performance Indicators (KPIs).

C. Prescriptive AI. It provides ways to improve net- work efficiency. Potential areas include using deep learning techniques for resource allocation, that cov- ers MAC resource allocation, scheduling, and resource management.

Among the twenty selected papers in this special issue, seven papers are mostly dealing with descriptive AI, while six papers focus on predictive approaches. Finally, seven papers are mainly related to prescriptive AI.

A. Descriptive AI in Communications Networks

In "Towards knowledge as a service over networks: a deep learning model communication paradigm", Chen et al. address the exchange of knowledge in IoT environments via neural network models [4]. They propose a deep-learning model com- munication paradigm based on multiple model compressions, that exploits the redundancy among multiple deep learning models in different application scenarios.

In "Deep transfer learning for intelligent cellular traffic prediction based on cross-domain big data", Zhang et al. focus on predicting cellular traffic, taking spatial and temporal features into account [35].

They develop a deep learning-based method which exploits transfer learning approach, thereby enabling their model to train on other available auxiliary datasets as well, in addition to main dataset, in order to make more accurate and robust prediction.

In “Idle time window prediction in cellular networks with deep spatiotemporal modeling”, Luoyang et al. study the idle time windows (ITW) prediction in mobile networks based on network subscribers’ demand and mobility behaviors observed by network operators [6]. A novel temporal-graph convolu- tional networks (TGCN) model is designed to characterize both the spatial and temporal relevance for the idle timewindow prediction. Experiments on real mobile signaldataset demonstrated the promising performance of TGCN.

The paper “AuDI: Towards autonomous IoT device-type identification using periodic communication” by Marchal et al. presents a system for quickly and effectively identifying the type of a device in an IoT network by analyzing their network communications [7]. The approach models the periodic communication traffic of IoT devices using an unsupervised learning method to perform identification allowing for the definition of common policies for classes of devices based on device type.

In “Energy-efficient distributed mobile crowd sensing: a deep learning approach”, Liu et al. propose a concept for navi- gating mobile terminals’ sensing and movement around points of interest minimizing their energy consumption [8]. The resulting control algorithm integrates Convolutional Neural Network (CNN) for feature extraction, and then makes deci- sions under the guidance of multi-agent deep deterministic policy gradient method in a fully distributed manner.

In “Data transmission reduction schemes in WSNs for efficient IoT systems”, Jarwan et al. focus on the problem of reducing energy consumption of continuous sensor data collection by exploiting the spatial and temporal correlation of the generated traffic in wireless sensor networks [9]. They compare and analyze several state-of-the-art machine learning algorithms that assess improvement in energy reduction with the machine learning approach.

In “A privacy-preserving-based data collection and analysis framework for IoMT applications”, Usman et al. propose a data collection and analysis framework for IoMT (Internet of Multimedia Things) applications using clustering of under- lying Wireless Multimedia Sensor Networks (WMSNs) into multiple clusters [10]. While cluster heads are responsible for protecting the privacy of member nodes through data and location aggregation, aggregated multimedia data is then analyzed at the cloud server using a counter-propagation artificial neural network to extract meaningful information through segmentation.

B. Predictive AI in Communications Networks

In “Dynamic TCP initial windows and congestion control schemes through reinforcement learning”, Nie et al. consider dynamic TCP performance control using the framework and techniques of reinforcement learning [11]. Depending on the network conditions, the initial window size and a congestion control scheme are chosen and dynamically adapted. Testbed experiments show the effectiveness of the proposed solution and gains over known control schemes.

The paper “Experience-driven congestion control: when multi-path TCP meets deep reinforcement learning” by Xu et al. introduces a framework for congestion control of multi-path TCP [12]. The framework is based on represen- tation learning and includes three different neural networks to dynamically control the congestion windows of all active flows in a host. The proposed framework is implemented in a Linux environment and is evaluated against several Multi-path TCP congestion control schemes. It performs well against thetraditional schemes regarding goodput and fairness in a broad range of scenarios.

In “Learning QoE of mobile video transmission with deep neural network: A data-driven approach”, Tao et al. aim to develop a data-driven approach to predict the quality of experience (QoE) in mobile video transmission [13]. They first construct a dataset for QoE of mobile video transmission and then propose a method to predict subjective QoE scores. A deep-neural network (DNN) is developed to learn the rela- tionships between the network parameters and the subjective QoE scores.

Jiang et al. address the problem of resource allocation in NB-IoT in their paper entitled “Reinforcement learning for real-time optimization in NB-IoT networks”. They provide several proposals using reinforcement learning to maximize the number of served IoT devices in dynamic environ- ments [14]. In the paper, the authors show that their approach requires less training time while the improvement of their algorithm using cooperative multi-agent learning outperforms other methods and converges to efficient solutions even at large scale.

In “Wireless traffic prediction with scalable Gaussian process: Framework, algorithms, and verification”, Yue et al. address wireless traffic prediction using ML techniques [15]. The proposed scalable Gaussian process (GP) framework can handle large-scale wireless traffic prediction with the con- sideration of computational complexity. Experiments on real base station traffic data demonstrated the effectiveness of the proposed method.

In “Anomaly-tolerant network traffic estimation via noise-immune temporal matrix completion model”, Xiao et al. provide a method to simultaneously estimate a network traffic matrix estimation and detect network anomalies based on a novel matrix completion model that can cope with noise and network anomalies [16].

C. Prescriptive AI in Communications Networks

In “Optimal and fast real-time resources slicing with deep dueling neural networks”, Huynh et al. focus on network slicing by considering the availability of resources such as radio, compute and storage in real-time. They develop a reinforcement learning algorithm which is based on a deep dueling approach allowing for the convergence rate to improve in large networks [17]. Based on a semi-Markov decision process, the solution provided by the authors outperforms conventional Q-learning algorithms as well as more elaborate approaches such as a double Q-learning model.

In “Adaptive federated learning in resource constrained edge computing systems”, Wang et al. address the problem of federated learning in distributed systems as exemplified by current network architectures such as Multi-access Edge Computing (MEC) [18]. They derive a mathematical formula- tion for learning model parameters that allows accounting for limited resource capability at the edge nodes while remotely coordinating aggregates in the cloud. In the paper, the authors consider a gradient-descent approach which is common to many machine learning methods and determine the optimal

trade-off between local update and global parameter aggregate to efficiently use constrained edge and network resources.

In "A reinforcement learning approach to energy efficiency and QoS in 5G wireless networks", Wang et al. focus on a game-theoretic approach to design a distributed energy- efficient bandwidth sharing mechanisms for small-cell net- works [19]. They develop two reinforcement learning-based approaches to strike a balance between energy efficiency and high bandwidth utilization.

In "Spatial deep learning for wireless scheduling", Cui et al. focus on scheduling interfering links in a wireless commu- nications network using deep learning-based framework and techniques [20]. The proposed spatial deep learning network gives the near-optimal performance for sum-rate maximization and is capable of generalizing to larger deployment areas and to deployments of different link densities.

In "Deep-reinforcement learning multiple access for hetero- geneous wireless networks", Yu et al. investigate the use of deep reinforcement learning in a MAC protocol for heteroge- neous wireless networking referred to as Deep-reinforcement Learning Multiple Access [21]. The proposed solution solves the problem of sharing time slots among a multiple of time-slotted networks that adopt different MAC protocols. Extensive simulation results show that the proposed solution can achieve near-optimal sum throughput and proportional fairness objectives, two special cases of α-fairness.

In "Online learning for energy saving and interference coordination in HetNets", Ayala-Romero et al. develop a two- level algorithm to jointly control energy saving and interfer- ence coordination mechanism based on a contextual bandit formulation to optimize the energy efficiency [22]. The control framework includes a global controller, in charge of a group of macrocell, and multiple local controllers, one per macro cell. The main benefit of this two-level scheme is the drastic reduction of the dimensionality of the learning problem.

In "Joint transceiver optimization for wireless communica- tion PHY using neural network", Zhu et al. propose a novel neural network structure for jointly optimizing the transmitter and receiver in communication physical layer under fading channels [23]. They propose a convolutional auto-encoder structure that is capable to automatically design communi- cation physical layer scheme according to different channel status. The system has no restriction on the length of input bit sequence. The experiment results give empirical evidence for the superiority of the proposed system.

II. RESEARCH CHALLENGES

In this section we outline research topics that have attracted less attention to date by the research community and lack representation in the selected papers for this issue. We believe they are of high potential and should be investigated to fully exploit AI/ML methods for networking and networked systems in general.

A. Effective Network Data Representation

Statistical learning allows us to create a model of a system from observations; the behavior of a system is learned throughmonitoring it over a satisfactorily long time. This insight leads to two research directions, in which one is currently actively pursued while the other one is largely unexplored. The first direction focuses on learning effective control policies and decisions. Such works generally address complex optimization or control problems where optimal solutions are intractable to compute. The learned models provide heuristic solutions whose quality depends on the learning methods used and the input data. Characteristic of these approaches is that the structure of the input data is clearly defined by the formal problem description and includes only a small number of data types or data sources.

The second direction of research is on data representation of the networked systems. Consider the problem of predicting or forecasting end-to-end metrics in a networked system, such as service-level KPIs or QoE metrics of network services. Due to the overall complexity of such systems, a formal model- based approach is generally not feasible and statistical learning has emerged as an attractive option. Data sources that can be selected for model computation are abundant and include logs, local metrics and statistics, as well as telemetry data. The number of data types (or sources) that are available for model computation can be very large and range from several dozens for a small system to billions for a large infrastructure. The problem thus becomes identifying and producing a data representation of the system from which efficient and accurate prediction models can be learned. (Finding such a representation is referred to as feature engineering in an AI/ML context.) In the case of networked systems, repre- sentations are built from a large set of heterogeneous and distributed data sources, often measured with various degrees of accuracy, read out at various rates, and degraded by missingor corrupted data.

An effective data representation should have low dimen- sionality, i.e., the number of data sources or aggregated metrics is kept low, which reduces the computation time for learning and decreases the number of observations needed for accurate prediction. How to find such representations has been thoroughly studied for cognitive tasks, such as image or voice recognition, but has not been addressed for network engineering.

Learning models based on deep architectures, such as deep neural networks, produce consecutive layers of data represen- tation, to which semantics like increasing levels of conceptual abstractions can be attributed. Again, such representations are well understood for cognitive tasks but have not been investi- gated or leveraged in the context of network engineering.

B. Integrated Decision-Making Into the Networks

The decision-making process in a networked system can be modeled as three consecutive sub-processes: monitoring, i.e., for estimating the state of a networked system and its evolution over time; learning/inference, which includes estimation and forecasting derived metrics; and control actions aimed at changing the system state following given policies. These subprocesses are currently studied, designed, and optimized in isolation. The challenge is to understand them as combinedactivities, develop integrated designs, and jointly optimize them.

Integrated decision-making is of particular importance in two contexts. First, in environments with limited commu- nication or computational resources where a fundamental understanding of the tradeoffs between overhead incurred by monitoring, learning, and control on the one side and the effectiveness of decision making on the other side becomes crucial. The second context relates to large-scale systems where data sources and control points are highly distributed. Many emerging networked systems fall into this category. While for small systems (i.e. up to dozens of nodes or data sources) centralized solutions are preferable due to design simplicity, for larger systems, distributed schemes must be investigated. In the recent literature, hierarchical schemes as well as methods using more general topologies have been proposed.

From a systems point of view, the

technology of soft- warization within telecom networks is expected to facilitate integrated decision making [24], [25]. The concept of network function virtualization (NFV), a key aspect of softwarization, allows to place a functionality in the network infrastruc- ture where resources are available and constraints are met. In addition, NFV facilitates the online change of functional configurations so that adaptive decision-making processes can be implemented.

C. Architectures for Learning From Network Data

Integrated decision making in networks must be supported by a dedicated architecture. As depicted in the previous section, network softwarization and NFV in particular facil- itate the placement and online adaptation of (virtualized) network functions. Research challenges with respect to AI/ML that arise from such network adaptation potential are twofold. First, in a softwarized network environment, the options and their parameters for placing and chaining functions become hardly tractable in today's large and complex networks. Hence, AI/ML methods can be used as tools to tackle the complexity and provide heuristic solutions to largely complex optimization problems.

Second, the network support for online decision making is an open research question. In order to facilitate the execution of AI/ML methods in network elements or distributed over several network elements, new architectures for program- mable network elements facilitating in-network processing are required. How can AI/ML be supported by network hardware and software? For example, well integrated GPU-based archi- tectures for fast computation of large data sets could be a possible solution.

D. Network Automation

As already hinted at in the previous section, the trend to higher programmability in wired and wireless networks as described by the potential of network softwarization opens up a plethora of new options for a fully flexible network operation, control and management. The Software-Defined Networking (SDN) concept supports the adaptation of networkflows, the Network Function Virtualization (NFV) concept supports the flexible split and allocation of functions, and network virtualization/slicing supports multiple heterogeneous applications in one network substrate. Whereas the three concepts have emerged for wired networks, their applica- tion for radio networks is currently an important research topic.

The aforementioned options result in a much higher com- plexity for network control and management as ever before. Hence, decision making becomes extremely difficult and algo- rithmically challenging. AI/ML methods are considered to provide efficient solutions here. First, they support heuris- tics outperforming existing optimization algorithms in terms of speed. Second, compared to existing heuristic solutions, AI/ML approaches provide the possibility to adapt to the actual network state without manual adaptation.

One step further, it is now commonly considered that future networks will operate autonomously, taking into account their own state, the state of the environment and their complex parameter options. AI/ML methods provide means for decision making to facilitate network automation. One example is self-driving networks which have to deal with the uncertainty of the data input such as arrival of flows, traffic volume, applications, hardware availability, etc. The desired property of a self-driving network is being prepared for challenges and requirements that come up in the future. That means a system is robust to changes in the environment and opens for new tasks without significant performance degradation.

E. Standardized Test Cases and Datasets to Assess AI/ML Solutions

Whereas the potential of applying AI/ML methods is obvi- ous, the evaluation and comparison of different solutions is difficult due to the lack of common test cases and datasets. Due to the heterogeneity of the problem space to be addressed by AI/ML, this is a challenging task for the research community. Nevertheless, it is of high importance to be able to assess AI/ML solutions properly to be able to understand their applicability to specific and generalized problem sets. Test cases describe a set of challenges that have to be solved by a system implementation, e.g. a trajectory for a UAV (Unmanned Aerial Vehicle), a sequence of network function embedding requests, etc. Data sets contain data that is representative and typical for a certain problem space.

We hope that the above-mentioned topics are providing useful food-for-thoughts to researchers and will result in many contributions to a future special issue of JSAC devoted to advances in artificial intelligence and machine learning for networking. The corresponding call for papers under prepa- ration should be more focused to address areas that have not been well embraced in this current issue.

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REFERENCES

[1] B. A. A. Nunes, M. Mendonca, X.-N. Nguyen, K. Obraczka, and

T. Turletti, "A survey of software-defined networking: Past, present, and future of programmable networks," IEEE Commun. Surveys Tuts., vol. 16, no. 3, pp. 1617–1634, 3rd Quart., 2014.

[2] Y. Li and M. Chen, "Software-defined network function virtualization: A survey," IEEE Access, vol. 3, pp. 2542–2553, Dec. 2015.

[3] R. Boutaba et al., "A comprehensive survey on machine learning for networking: Evolution, applications and research opportunities,"

J. Internet Services Appl., vol. 9, no. 1, p. 16, Jun. 2018.

[4] Z. Chen et al., "Towards knowledge as a service over networks: A deep learning model communication paradigm," IEEE J. Sel. Areas Commun., to be published.

[5] C. Zhang, H. Zhang, J. Qiao, D. Yuan, and M. Zhang, "Deep transfer learning for intelligent cellular traffic prediction based on cross-domain big data," IEEE J. Sel. Areas Commun., to be published.

[6] L. Fang, X. Cheng, H. Wang, and L. Yang, "Idle time window prediction in cellular networks with deep spatiotemporal modeling," IEEE J. Sel. Areas Commun., to be published.

[7] S. Marchal, M. Miettinen, T. D.

Nguyen, A.-R. Sadeghi, and N. Asokan, “AuDI: Towards autonomous IoT device-type identification using periodic communication,” IEEE J. Sel. Areas Commun., to be published.

[8] C. H. Liu, Z. Chen, and Y. Zhan, “Energy-efficient distributed mobile crowd sensing: A deep learning approach,” IEEE J. Sel. Areas Commun., to be published.

[9] A. Jarwan, A. Sabbah, and M. Ibnkahla, “Data transmission reduction schemes in WSNs for efficient IoT systems,” IEEE J. Sel. Areas Commun., to be published.

[10] M. Usman, M. A. Jan, X. He, and J. Chen, “A privacy-preserving-based data collection and analysis framework for IoMT applications,” IEEE J. Sel. Areas Commun., to be published.

[11] X. Nie et al., “Dynamic TCP initial windows and congestion control schemes through reinforcement learning,” IEEE J. Sel. Areas Commun., to be published.

[12] Z. Xu, J. Tang, C. Yin, Y. Wang, and G. Xue, “Experience-driven congestion control: When multi-path TCP meets deep reinforcement learning,” IEEE J. Sel. Areas Commun., to be published.

[13] X. Tao, Y. Duan, M. Xu, Z. Meng, and J. Lu, “Learning QoE of mobile video transmission with deep neural network: A data-driven approach,” IEEE J. Sel. Areas Commun., to be published.

[14] N. Jiang, Y. Deng, A. Nallanathan, and J. A. Chambers, “Reinforcement learning for real-time optimization in NB-IoT networks,” IEEE J. Sel. Areas Commun., to be published.

[15] Y. Xu, F. Yin, W. Xu, J. Lin, and S. Cui, “Wireless traffic prediction with scalable gaussian process: Framework, algorithms, and verification,” IEEE J. Sel. Areas Commun., to be published.

[16] F. Xiao, L. Chen, H. Zhu, R. Hong, and R. Wang, “Anomaly-tolerant network traffic estimation via noise-immune temporal matrix completion model,” IEEE J. Sel. Areas Commun., to be published.

[17] N. V. Huynh, D. T. Hoang, D. N. Nguyen, and E. Dutkiewicz, “Optimal and fast real-time resource slicing with deep dueling neural networks,” IEEE J. Sel. Areas Commun., to be published.

[18] S. Wang et al., “Adaptive federated learning in resource constrained edge computing systems,” IEEE J. Sel. Areas Commun., to be published.

[19] Y. Wang, X. Dai, J. M. Wang, and B. Bensaou, “A reinforcement learning approach to energy efficiency and QoS in 5G wireless networks,” IEEE J. Sel. Areas Commun., to be published.

[20] W. Cui, K. Shen, and W.Yu, “Spatial deep learning for wireless scheduling,” IEEE J. Sel. Areas Commun., to be published.

[21] Y. Yu, T. Wang, and S. C. Liew, “Deep-reinforcement learning multiple access for heterogeneous wireless networks,” in Proc. IEEE Int. Conf. Commun., May 2018, pp. 1–7.