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Artificial Intelligence to Manage Network Traffic of 5G Wireless Networks

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Abstract

The deployment of the fifth generation (5G) wireless communication systems is projected for 2020. With new scenarios, new technologies, and new network architectures, the traffic management for 5G networks will present significant technical challenges. In recent years, artificial intelligence (AI) technologies, especially machine learning (ML) technologies, have demonstrated significant successes in many application domains, suggesting its potential in helping to solve the problem of 5G traffic management. In this article, we investigate the new characteristics of 5G wireless network traffic, and discuss challenges they present for 5G traffic management. Potential solutions and research directions for the management of 5G traffic, including distributed and light-weight ML algorithms and a novel AI assistant content retrieval algorithm framework are discussed.

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I. INTRODUCTION

The fifth generation (5G) wireless communication networks are on their way to final deployment. The 5G wireless networks will offer ultra-fast and reliable wireless links [1]. The deployment of 5G will drive global mobile data traffic to 100 exabytes per month by 2023 from 31.6 billion mobile devices, which is nearly double the present level [2]. In the future 5G networks, the system complexity in terms of network architecture and wireless connection will increase substantially. On the other hand, the average accessible resource for each user/device will be rather limited. Consequently the explosive increase in data volume and user devices will bring significant challenges to the management and optimization of network traffic.

Current research on 5G network traffic management has already driven conventional approaches purely based on communication theory to the limit. It will be extremely challenging to solve the traffic problem of 5G networks and to achieve the global optimal performance of the whole network. This suggests the need to adopt revolutionary solutions.

A promising direction to tackle the challenges described above is to adapt artificial intelligence (AI) technologies to analyze and manage the traffic of 5G networks from network data [3]. AI technologies will not only reduce manual interventions in network traffic management, but also enable better network performance, better reliability, and more adaptive systems by drawing new insights of the networks and predicting the network traffic condition and the user behavior for smarter decisions in an autonomous fashion.

Machine learning (ML) and Deep learning (DL), as two advanced AI methodologies, have attracted lots of interest in the use of big data to overcome the challenges of managing 5G networks traffic [5]–[7]. However, existing research has highlighted following limitations:

- (i) Most existing reported research has only focused on the core network, and applied ML to solve the routing problem in the core network, there is few research on traffic control with respect to the 5G network.

- (ii) For traffic control, most works only focused on the network layer, there is few research on applying AI technologies to the application layer and the semantic layer that shape the traffic by content recommendation with considerations of user interests.

In this article, we investigate the new features and challenges in 5G wireless traffic caused by new scenarios, network architectures, and new service demands. Based on these analyses, we will propose potential solutions and research directions based on AI technologies.

The remainder of this paper is organized as follows. Section II introduces potential challenges in future 5G networks. Section III and IV introduce deep-reinforcement learning and distributed and light-weight ML algorithms for 5G network traffic control. An AI assistant traffic shaping algorithm is highlighted in Section IV. Finally, conclusions are drawn in Section VI.

II. NEW FEATURES AND CHALLENGES OF NETWORK TRAFFIC IN 5G WIRELESS NETWORKS

A. *New features and challenges in 5G traffic caused by new scenarios*

Defined by the International Telecommunication Union (ITU), future 5G systems will have three major scenarios. First, the Enhanced Mobile Broadband (eMBB), which aims for getting extremely high data rate to fulfill the high-speed data access requirement of emerging services such as three-dimensional (3D) and ultra-high-definition (UHD) video transmission, and virtual reality (VR) applications. Second, the massive machine type communications (mMTC), which aims to provide high connection density (up to 200,000 devices/km²) low data rate (1 to 100 kbps per device) at low power consumption (up to 15 years battery life) to fulfill requirements of sensor networks used for smart city, Internet of things (IoT), and wearable devices networks. Third, the ultra-reliable low latency communication (URLLC) scenario that aims to provide extremely high reliability (99.999 %) and low latency (<1ms) wireless services used for control networks such as high-speed train control, transport safety control, remote medical surgery services, and industry robotic control, etc..

For these three scenarios, due to their different service foci, their data traffic characteristics are significantly different. For the eMBB scenario, in order to achieve an extremely high data rate for each user, the package size will be large and most data will be transmitted in the down-link direction. For the mMTC scenario, most data will be transmitted in the up-link direction. Due to the high density of low data rate devices, the traffic of mMTC scenario is largely discrete. For the URLLC scenario, in order to fulfill the requirement of the low delay and high reliability, the data package size will be small, the transmission time interval (TTI) will be short, and a short frame structure with hybrid automatic repeat request (HARQ) will be used.

Due to the more frequent feedback to guarantee delivery success, lots of traffic will occur in the up-link direction, which makes the traffic of URLLC scenario likely to appear balanced between the down-link and the up-link direction. In Table I, we summarise the system performance requirement and traffic features of the three major 5G scenarios.

In the core network, all of the above type of data will be mixed. Due to the inherent traffic features of these three major 5G scenarios which are significantly different, the traffic will be very dynamic and unpredictable. It is hard to predict the traffic condition and make optimization using conventional traffic control method, even with the assistant of some existing model-driven ML methods.

B. New features and challenges of 5G traffic caused by new network structures

In the future 5G network, the software-defined networking (SDN) will be used as a key technology. By using SDN, the control and data plan can be naturally isolated, the network management work can be achieved through software-based application program interfaces rather than hardware dependent configurations. It can minimize hardware constraints, support speedy service provisioning, and promise network flexibility. Benefited from the feature of SDN, network slicing will be deployed for the 5G networks, which can support multiple virtual network functions running on a unified infrastructure. In the completed 5G network, eMBB, URLLC, and

mMTC services will be independently operated on a unified physical infrastructure. However, due to the different performance requirements, there is a significant difference in network slicing. In order to provide high-speed large volume data access to users, and to relieve the pressure on backbone networks, the eMBB slicing tends to bring the data closer to users. It generates significant requirements for the resource to deploy cache in the mobile cloud engine of the local data centers (DCs). Thus for THE eMBB scenario, the pressure of traffic will mainly occur in the down-link direction between the local DC and the user equipment (UE). For the URLLC slicing, as it has strict requirements on latency and reliability, its processing function units must be deployed to UE as close as possible. A possible solution is that allocated data processing units in the mobile cloud engine of the central office DC to support highly frequent, small packet transmission over a short distance. As a result, the traffic pressure of URLLC slicing will mainly occur between the central office DC and the UE. For mMTC slicing, there will be a smaller amount of network data interaction of each UEs. However, due to the high connection density, its main traffic will occur in the up-link direction of the radio access network. All the data will be combined in the local DC and transmitted to the IoT server in the regional DC through the core network. If we consider the large volume of IoT data, the link between the local DC and regional DC may also bring some challenges. In Fig. 1, the network structure of the 5G network is shown.

Based on these statements, we can predict following two challenges for network traffic management caused by new network structures of 5G networks.

- (i) The 5G wireless network will be a heterogeneous network. The coexistence of different networks and the mixture of their traffic data with significantly different characteristics, making the prediction, management, and the optimization of network traffic a difficult task.
- (ii) As the SND technology will be used by the 5G network, and its feature of network function virtualization (NFV) and network slicing will be deployed, all services will be indepen-

dently operated on a unified physical infrastructure. However, as all traffic will finally be mixed with each other, and the traffic features of different scenarios are significantly different, the mixture of all these networks traffic will make the network unpredictable.

C. New features and challenges of 5G traffic caused by new network services

In the 5G era, the human behavior of using wireless networks will change dramatically, which will result in an explosive increase on traffic data. Due to the rapid increase of content-centric applications (e.g., social media applications) [8], data service by content-retrieval applications has become a major consumer of traffic on the mobile Internet. In current networks, data is still mainly stored in the centralized data center. For all access, data still needs to be transmitted from the DC to the UE through the core network and the radio access network (RAN). While in the 5G network, in order to decrease the delay and relieve the pressure of core network traffic, data including recommended content will first be stored in the cache in the mobile cloud engine of a local data center (eMBB scenario). In this case, the traffic feature of content-centric applications will change from constant core network access to randomly core network access, which is beyond existing studies on core traffic control.

III. MACHINE LEARNING FOR 5G NETWORK TRAFFIC CONTROL

The new scenarios and features of 5G network traffic detailed above raise a series of challenges for conventional traffic control strategies. To overcome these challenges, a large number of sophisticated decision making and inference processes are required to adaptively allocate/manage network resources, smartly schedule/choose routing strategies and promptly predict traffic condition for 5G networks. ML, particularly recent advances in DL, offers promise in tackling these problems. In this section, we discuss 5G network traffic control from the perspective of three types of machine learning algorithms: supervised learning, unsupervised learning, and

reinforcement learning. Since there are some surveys on supervised and unsupervised learning in existence [3], we focus on reinforcement learning.

A. A Supervised Learning Perspective

Supervised learning [10] relies on a set of training samples labeled by a knowledgeable external supervisor to train a model, see Fig. 2(a). The training data defines a mapping between the inputs and the desired labels for classification or regression problems. The model is then expected to infer reasonably for new input examples. Supervised learning has been reported in selecting the network routing path, and predicting traffic volume, etc. Recently, deep learning, e.g., convolutional neural networks, have also been demonstrated to achieve a more effective network traffic management than traditional routing methods. However, supervised learning is usually expensive and labor-intensive to manually annotate large-scale training data for vast, heterogeneous 5G networks. For some traffic control problems, it is challenging to employ supervised learning since it is not always possible to find global optima for data annotation. Therefore, it would be more appealing to learn without the need of labelling.

B. A Unsupervised Learning Perspective

Unsupervised learning aims to find and understand data structure automatically without external supervision. As shown in Fig. 2(b), it can be used for clustering problem. It has been widely used to reduce data complexity, model data distribution, and detect network anomalies, etc. Unsupervised learning for 5G network traffic control can facilitate probability modeling of the traffic pattern, congestion and traffic conditions to the eMBB, mMTC and URLLC scenarios. Therefore, not only the status of the network traffic can be better forecast, but also the network scheduling and configuration can be pre-set and adaptive to the network traffic and topology changes.

C. A Reinforcement Learning Perspective

Reinforcement learning (RL) [11] enables an agent to automatically learn an optimal decision by continuously interacting with its environment and maximizing its cumulative reward. Combining with DL, it can be a general-purpose framework tackling problems that are previously intractable, especially in complex settings with high-dimensional state and action spaces. This new paradigm, termed deep reinforcement learning (DRL), has been demonstrated to build AlphaGo, which defeated a world champion at the game of Go. It has great potential to deliver intelligent traffic control systems for heterogeneous, ultra-dense 5G networks with highly dynamic topologies [12].

In general, DRL contains three major elements: *a*) a policy function which defines the agent's behavior; *b*) a value function which evaluates how good each state and/or action is; and *c*) a model of the environment which represents agent's learned knowledge of the environment. As shown in Fig. 3, in the context of network traffic control, an agent as the traffic control algorithm learns from direct interactions with its environment representing the 5G network. The agent senses the state of the environment to some extent and takes actions, e.g. selecting the routing protocols, that affect the state. By interacting with the environment and discovering which actions yield the greatest reward, the agent gradually learns the optimal policies. The reward can be determined by communication congestion, latency, and packet loss, etc. One typical DRL algorithm is Deep Q-Networks (DQN) which represents the value function with a deep neural network. Note that reinforcement learning is different from supervised learning which is not concerned with interaction and reward. It is also different from unsupervised learning which usually focuses on how to discover hidden structure of unlabeled data.

Based on this DRL architecture, adaptive and intelligent network traffic control algorithms can be developed. The agent learns how to deliver a package to its destination as quickly and robustly as possible by reducing the latency and network congestion. Since no labeled data is needed,

this algorithm can learn adaptive strategies automatically. More importantly, it enables a lifelong learning capability for the traffic control system. Specifically, when excessive traffic delay and heavy congestion degrade the network performance, conventional traffic control systems cannot learn from the experience or understand the situation for future. In contrast, DRL based methods can learn routing information and traffic patterns from this experience and successfully manage the massive network traffic the when this situation occurs next time. This means DRL based traffic control systems can evolve their performance continually over time and eventually be adequate to various scenarios.

Existing work has shown the effectiveness of RL based traffic control and routing of wireless sensor networks. However, to the best of our knowledge, there is no work on 5G network traffic control based on DRL.

D. Dataset and training for machine learning models in 5G networks

Data is essential to train ML models. However, different from the fields (e.g., computer vision) where ML techniques have been widely adopted, the wireless communication community has very limited access to large-scale datasets for designing ML models by now. This hinders the development and application of ML models in wireless communication.

1) Dataset: There are several possible means to generate dataset for 5G networks. For supervised learning, simulation is a low-cost option with ground truth being directly available for many traffic control applications. However, the generalization ability needs to be carefully evaluated when deploying the trained models in reality since the 5G networks and their scenarios are too complex to be accurately simulated. Alternatively, the training labels can be generated from traditional methods and a self-supervised learning mechanism can be utilized. However, the quality of the training data highly depends on the performance of the traditional methods used to generate labels. Besides, for traffic control and management of 5G wireless networks, there are still many open challenges and no effective solution exist yet. In contrast, RL is more

appealing as it does not need labels for training. It can be simply trained with rewards which are determined by the requirements on the traffic control. More importantly, the data collection and model training can take place online with lifelong learning through continuously interacting with the environments. This is one of the big advantages of RL for 5G networks.

2) *Training*: The training of ML models for 5G networks can vary greatly, according to where the trained model to be deployed and which type of ML algorithms is used. The training can be carried out on high performance computing (HPC) clusters, the network embedded systems (e.g., end-user devices), and cloud computing servers. For supervised learning, models are usually trained offline with prepared dataset on HPC and deployed later in the 5G networks. Depending on where they are going to be hosted, some parts of the 5G networks may have to be temporarily out of service for model testing and deployment. RL training does not have this problem since it runs and interacts simultaneously with the services of the 5G networks. Therefore, the training procedure needs to be inherent in the 5G networks. More importantly, the performance of RL improves over time while consistently exploring its optimal policies.

IV. DISTRIBUTED AND LIGHT-WEIGHT ML ALGORITHMS FOR OPTIMIZING TRAFFIC IN 5G mMTC AND ULLRC SCENARIOS

Existing ML algorithms mainly focus on computer vision, natural language processing and robotics with powerful graphics processing unit (GPU) or central processing unit (CPU) enabled computing to operate in real-time. However, communication systems are full of resource-constrained devices, e.g. embedded and IoT systems, especially in the mMTC scenario. Therefore, the AI algorithms for communication networks should not only learn complex statistical models that underlie networks, consumers, and devices, but also effectively work with embedded devices having limited storage capabilities, computational power and energy resources. It is challenging yet highly rewarding to develop light-weight ML algorithms, especially DL models, for embedded systems.

In current applications, AI algorithms are typically executed centrally in one single node (in

a centralized location) with full access to the global dataset and a massive amount of storage and computing. While in the 5G mMTC scenario as millions of devices will be connected in a high density, it is impossible to transfer all data from every single terminal to a center. Also for the URLLC scenario, due to its requirement for high reliability and low latency, data should be processed as close to the user as possible. However, due to the limit computing capability of IoT devices, it is impossible to run conventional centralized ML algorithms in one single device.

Currently, following existing technologies have been studied to enable the development of distributed and light-weight ML algorithms for wireless communications:

- (i) Advanced parallel computing for mobile devices, such as the Tegra GPU device from Nvidia, which will provide
- (ii) Novel distributed computing scheme, such as Fog computing, and Edge computing,
- (iii) High-level deep learning development library and tool box for embedded devices, such as TensorFlow Lite
- (iv) Emerging distributed machine learning frameworks, such as the geo-distributed ML system (Gaia) [13]

In Fig. 4, a potential deployment scheme of distributed and light-weight ML algorithms for 5G wireless networks is shown. In this framework, the Cloud computing, the Fog computing and the Edge computing have been considered. For the cloud server, as it has more computation capability, complex centralized large-scale ML algorithms will be run here. For fog computing node, as its computing capability is limited, light-weight ML algorithms will be run here. For Edge computing node, due to its extremely limited computing capability and power constraint, it is impossible for a single node to run the entire ML algorithm, thus distributed light weight algorithms will be run here.

V. AI ASSISTANT CONTENT CACHING, RECOMMENDATION, AND DELIVERY ALGORITHMS FOR TRAFFIC SHAPING IN 5G NETWORKS

In general, a personalized content retrieval service has two basic tasks: content recommendation and content delivery. The first task is to predict the interest of the user based on contextual information such as the user's historical preference, social relationships, location, etc, and recommend content that the user might be interested. The second task is to deliver the contents to users with quality-of-service (QoS) guarantee. Based on this statement, we can find the user's quality-of-experience (QoE) of a personalized content retrieval service is determined by two parts.

- (i) Whether the content recommendation is accurate and able to catch the interest of the user.
- (ii) Whether the process of accessing recommend contents is convenient and smooth.

Recently some researchers have used AI technologies to improve the performance of content retrieval service systems, most work is focused on using AI technology in the semantic layer to improve the accuracy of content recommendation. For the content delivery task, most existing papers have considered it as a communication issue and separated it with the recommendation task. However, it has been proved that joint optimization over recommendation and transmission will bring a greater improvement on QoE. In this condition, besides the accuracy, the data access experience will be considered as an issue of content recommendation. In good traffic conditions, content in the format of large volume transmit data such as HD video and will be recommended to the user, while in the congested traffic situation, contents with a small size such as the text, the simple web page will be recommended.

Previous research has mostly focused on the single user's QoE in existing wireless networks. In 5G networks, in addition to the user's QoE, the efficiency of data access also needs to be considered as it has significant influence on the traffic feature of the whole network. Here, we propose a content ML assistant recommendation algorithm framework in 5G networks to optimize the data transmission efficiency and shaping the data traffic from the application layer.

In the 5G network, especially for the eMBB scenario, data will be brought closer to the user. So in content retrieval, most recommended content will be stored in the cache of mobile cloud engine at local DC. The basic principle of this algorithm is to try to use as much local data as possible, if more data need to be transmitted from another location through the core network, its requirement in time and the current traffic will firstly be reviewed. The procedure of the algorithm is shown in Fig 5. First, the requirement for potential user interested content is obtained from the semantic layer, then the local controller will check what local content is valid, and evaluate whether this content is sufficient. If these contents are sufficient, the controller will select highly relevant content with high quality and recommend them to the user. It is necessary to note that the controller can use all local no-confidential data to serve its different users. If more data should be transmitted from other data center, the controller will first check the current traffic status of the network and the urgency of transmission, then decide the time slot and the format of contents to be transmitted. In this scheme, ML algorithms will be used for user requirement analysis, content recommendation, making data transmit decision, and traffic predictions. By using this algorithm scheme, on the basis of guaranteed user's QoE, we can provide a novel traffic optimization through the traffic shaping feature of AI assistant content retrieval service.

VI. CONCLUSIONS

In this article, we have discussed the traffic characteristics of 5G networks, and discussed the challenges they will present to the traffic management of 5G networks caused by new scenarios, new network architectures, and new network services. ML for 5G traffic control includes supervised learning, unsupervised learning and deep reinforcement learning for managing 5G traffic have been introduced. Distributed and light-weight ML algorithms for optimizing the up-link traffic in 5G mMTC and ULLRC scenarios have been discussed. A novel AI assistant content retrieval algorithm framework for optimizing the data traffic in the content retrieval services of future 5G networks has also been proposed. There are many further opportunities that will arise

for the use of AI and ML techniques in future 5G networks.

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TABLE I
TECHNICAL PERFORMANCE REQUIREMENT AND TRAFFIC FEATURES OF 5G MAJOR SCENARIOS.

5G Key Scenarios	Key System Performance Requirements	Traffic Features and Challenges
eMBB	Peak Data Rate: DL: 20 Gbps, UL: 10 Gbps User Experienced Data Rate: DL: 100 Mbps, UL: 50 Mbps (Dense Urban) Area Traffic Capacity: DL: 10 Mbps/M Latency: 4 ms	High data rate every user; Down-link-dominated transmissions traffic; Big data package transmission
URLLC	Latency: 1 ms Reliability: 99.999%	Strict requirements on latency and reliability; Frequently, short path, small package transmission
mMTC	Connection density: 1 million devices/ km ²	Low data rate every user; High connection density; Up-link-dominated transmissions

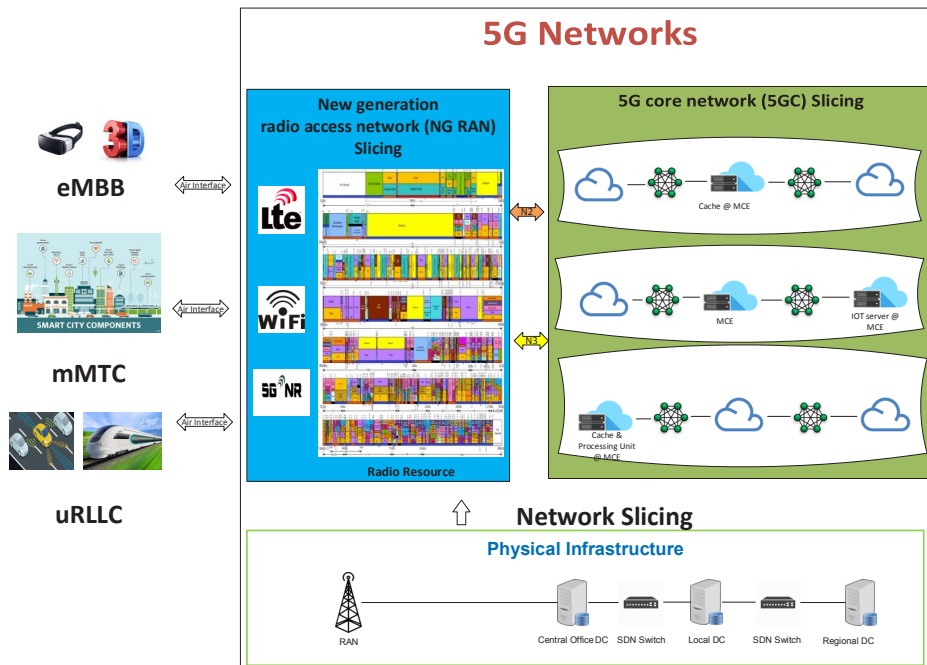
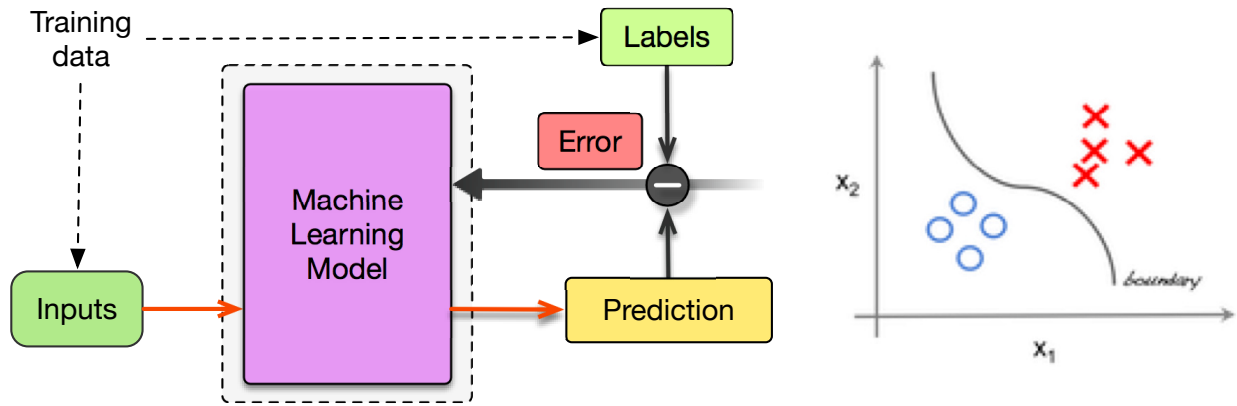
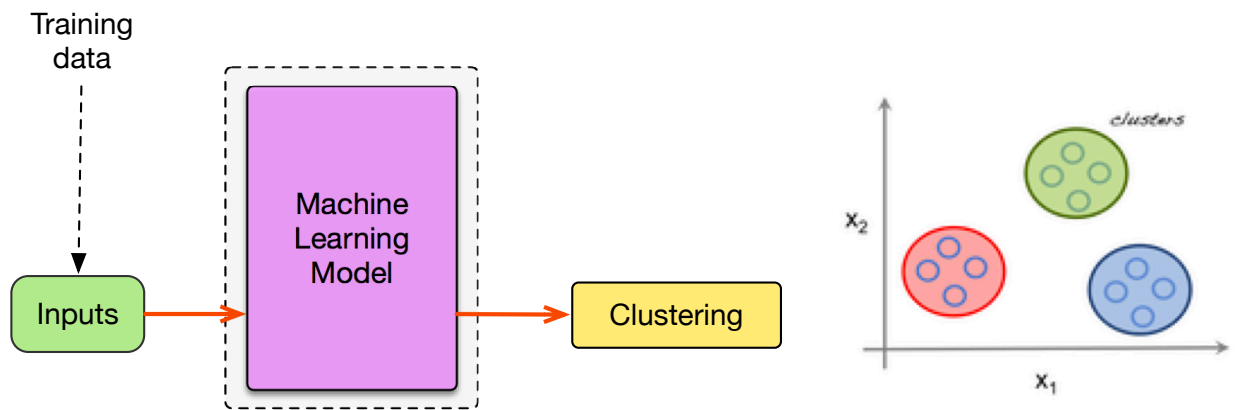


Fig. 1. New 5G network architecture.



(a) Supervised Learning.



(b) Unsupervised Learning.

Fig. 2. Supervised learning and unsupervised learning.

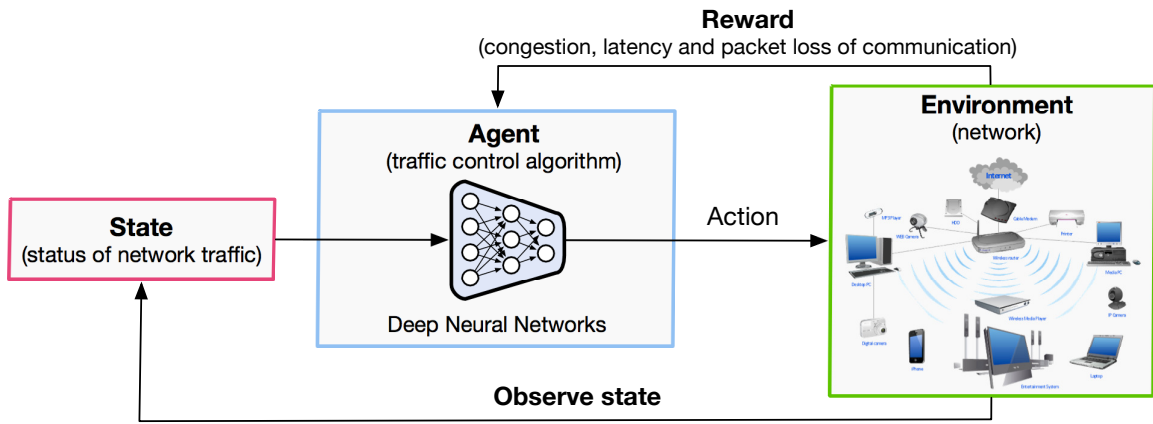


Fig. 3. Deep Reinforcement Learning in the context of network traffic control.

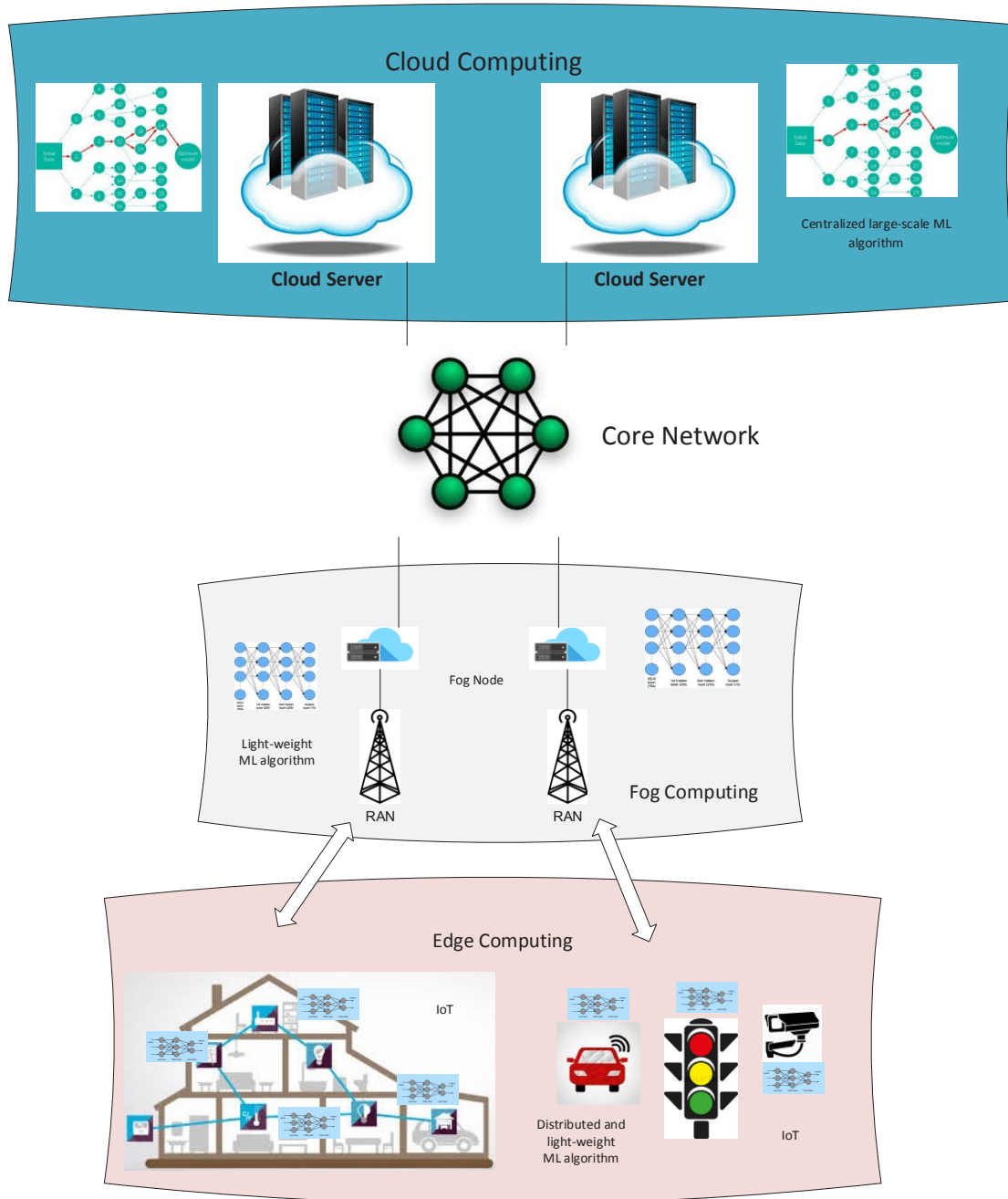


Fig. 4. Distributed and light-weight ML algorithms in 5G.

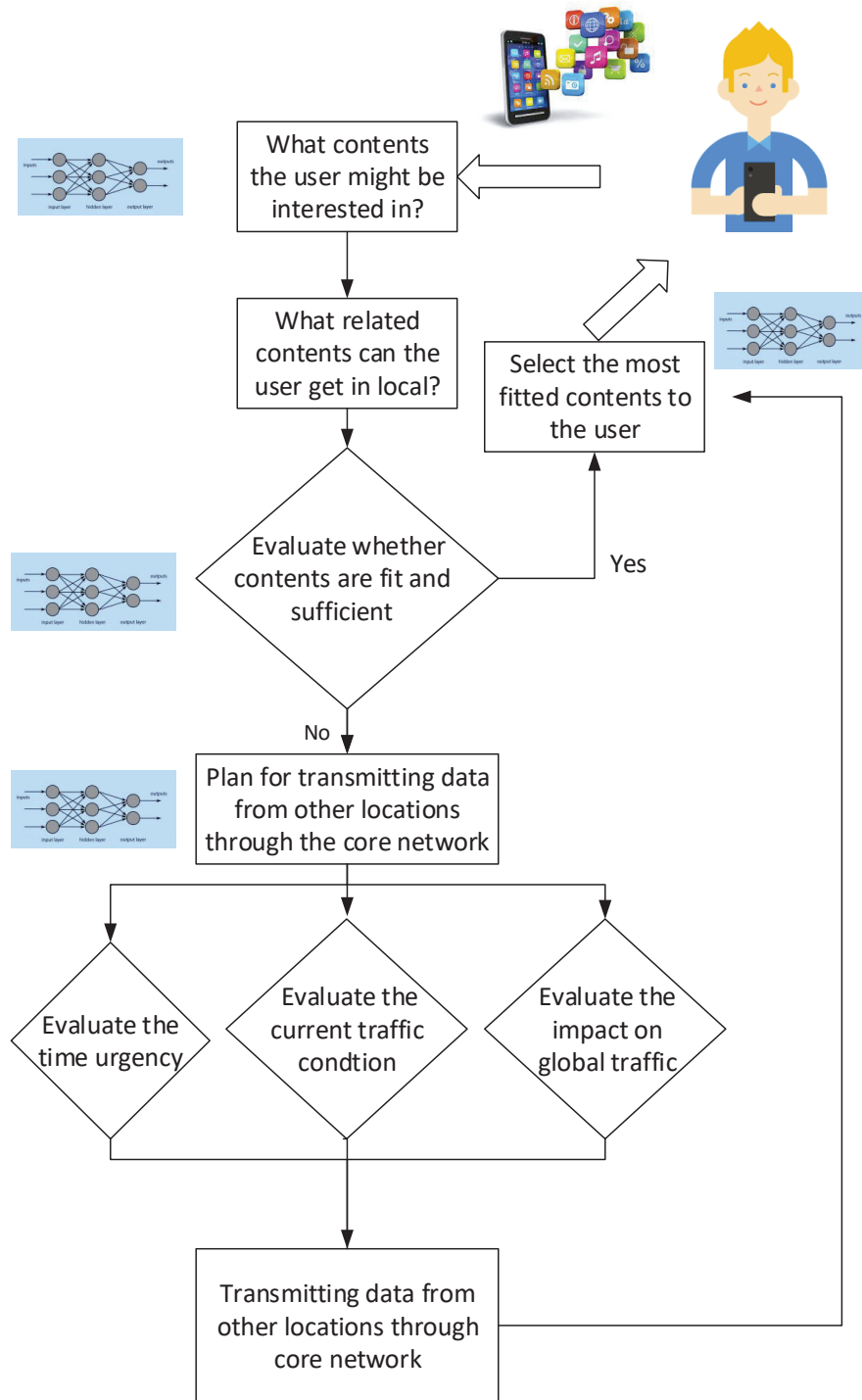


Fig. 5. AI assistant content retrieval algorithm frame work.