Deep Learning and AI for 5G Technology: Paradigms

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Abstract. Nowadays Internet of Things (IoT) is a major paradigm shift that will mark an epoch in communication technology such that every physical object can be connected to the Internet. 5G makes a significant breakthrough in the traditional mobile communication system and support the applications of IoT in various fields including business, manufacturing, health care and transportation.
5G is increasing the service capability of future IoT and operates and connects the whole society. 5G is facing enormous challenges when it supports differentiated applications with a uniform technical framework. In recent years, Artificial Intelligence (AI) is rising to these challenges with the rapid development. It is a potential solution to the problems in the 5G era and will lead to a revolution in the capabilities and concepts of the communication systems. Many researches have already been done for applying AI in 5G. In this paper, we focus on clarifying the promising research directions with the greatest potential rather than trying to review all the existing literatures. In this research, 5G can be anticipated to achieve significantly better performance and more convenient implementations compared to the traditional communication systems. With the inspiring research paradigms introduced in this paper, we are looking forward to the remarkable achievements of AI in 5G in the near future.

Keywords: Artificial Intelligence, IT Convergence, Machine Learning, Deep Learning, 5G Networks.

1 Introduction

Artificial Intelligence is great for problems in which existing solutions require a lot of hand-tuning or long lists of rules, for complex problems for which there is no good solution at all using traditional approaches, for adaptation to fluctuating environments, to get insights about complex problems that use large amounts of data, and in general to notice the patterns that a human can miss [1]. Hard-coded software can go from a long list of complex rules that can be hard to maintain to a system that automatically learn from previous data, detect anomalies, predict future scenarios, etc. These problems can be tackled adopting the capability of learn offered by AI along with the dense amount of transmitted data or wireless configuration datasets.

We have witnessed explosive growth in AI, mobile and computing systems becoming an essential social infrastructure, mobilizing our daily life and facilitating the digital economy in multiple shapes [2]. Certain applications available in this intersection of fields have been addressed within specific topics of AI and next- generation wireless communication systems. Li et al. [3], highlighted the potentiality of AI as an enabler for cellular networks to cope with the 5G standardization requirements. Authors in [4, 33], discussed the Machine Learning (ML) techniques in the context of fog (edge) computing architecture, aiming to distribute computing power, storage, control and networking functions closer to the users. Jiang et al. [5], focused on the challenges of AI in assisting the radio communications in intelligent adaptive learning, and decision-making. The next generation of cellular communication technologies also requires the use of optimization to minimize or maximize certain objective functions like spectrum utilization, data rates or energy consumption. Many of the problems in cellular communications are not linear or polynomial, in consequence, they demand to be approximated. Artificial Neural Networks (ANN) are an AI technique that has been suggested to model the objective function of the non- linear problem that requires optimization [6]. 5G networks will offer various applications and services compared to 4G and hence is more challenging with the complicated compatibility issues and evolving service requirements. Before 5G, researches of communication systems mainly aim at enhancing data transmission rate and efficient mobility management. In the 5G era, the communication systems will have the abilities to interact with the environment, and the optimizations of ever-increasing numbers of Key Performance Indicators (KPIs) like latency, reliability, connection density, user experience, etc. would be very important [7]. The field of AI research was born in 1950s, which went through varied interests and is revived in recent years due to the rapid development of modern computing and data storage technologies. The general problem of simulating intelligence contains sub-problems like reasoning, inference, data fitting, clustering and optimization, which involves approaches including genetic algorithms [8] and ANN [9-11]. Specially, AI learning techniques are universally applicable for various problems and are increasingly used in different fields. In the work [35] AI learning tasks are typically classified into two broad categories, supervised and unsupervised learning, depending on whether labels of the training data are available to the learning system. And another learning approach, reinforcement learning, is not exactly supervised neither unsupervised, hence can be listed in a new category. In this paper, we introduce the potential of AI algorithms into the next generation i.e 5G wireless networks to solve the requirements of the 5G standards so that they operate in a fully automated fashion, they provide increased capacity demand and they serve the users with superior Quality of Experience (QoE). This paper is divided according to the level of supervision the AI technique. The major categories discussed in the following sections are in supervised learning, unsupervised learning, and reinforcement learning. Reinforcement Learning interacts with the environment, getting feedback loops between the learning system and its experiences, in terms of rewards and penalties [5,13,22].

2 Supervised learning in 5G mobile and wireless communications technology

In this approach, the goal is to learn a general function that related the inputs to the outputs and then detects the unknown outputs of the future inputs. sample data of inputs and desired outputs are fed into the computer. According to works [10], the typical well-known example of supervise learning is illustrated in figure 1. In supervised learning, each training example has to be fed along with their respective label. In this example the labeled data pairs are fed in a multi-layer Deep Neural Network (DNN) to train the weights between the nodes in the DNN. The training is carried out offline, and after convergence, the trained DNN will be ready for recognition and inference of new inputs. A typical task on supervised learning is to predict a target numeric value, given a set of features, called predictors. This description of the task is called regression. The notion is that training a learning model on a sample of the problem instances with known optimal and then use the model to recognize optimal solutions to new instances.

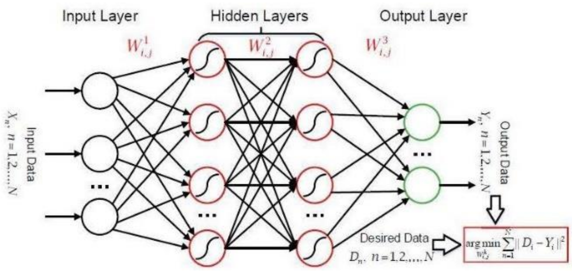

Fig. 1. Example of supervised learning: learning in deep neural networks [10].

Transfer Learning is a popular technique often used to classify vectors. Essentially, one would train a Convolutional Neural Network (CNN) on a very large dataset, for example ImageNet [9-10], and then fine-tune the CNN on a different vector dataset. The advantage of this approach is that the training on the large dataset is already done by some researchers who offer the learned weights for future research use. Another typical task of Supervised Learning is regression or prediction. The key difference between classification is that with ML algorithms like Logistic Regression, the model can output the probability of that certain value belongs to a given class. This type of system is trained with multiple examples of a class, along with their label, and the model must learn how to classify new instances [28-32]. Long Term Evolution (LTE) small cells are nowadays deployed in 5G networks to meet the ever-increasing high traffic demands. These small size cells are characterized by its unpredictable and dynamic interference patterns leading to different S/I ratios, expanding the demand for self-optimized solutions that can lead to lower call drops, higher data rates, and lower cost for the cellular operators. An extensive interest in path-loss prediction has raised since researchers noticed the power of AI to model more efficient and accurate path-loss models based on publicly available datasets [11]. Timoteo et al. [12], proposed a path loss prediction model for urban environments using support vector regression to ensure an acceptable level of Quality of Service (QoS) for wireless network users. They employed different kernels and parameters over the Okumura-Hata model and Ericsson 9999 model, and obtained similar results as a complex neural network, but with a lower computational complexity thereby saving time and memory.

Wireless communications depend heavily on wireless Channel State Information (CSI) to make an accurate decision in the operations of the network and employ digital signal processing. Liu et al. [13], investigated the unobservable CSI for wireless communications and proposed a neural-network-based approximation for channel learning, to infer this unobservable information, from an observable channel. Their framework was built upon the dependence between channel responses and location information. To build the supervised learning framework, they train the network with channel samples, where the unobservable metrics can be calculated from traditional pilot-aided channel estimation. The applications of their work can be extended to cell selection in multi-tier networks, device discovery for Device-to-Device (D2D) communications, or end-to-end user association for load balancing, among others. Sarigiannidis et al. [14], used a machine-learning framework based on supervised learning on a Software-Defined-Radio (SDR)- enabled hybrid optical wireless network. The machine-learning framework receives the traffic-aware knowledge from the SDN controllers and adjusts the uplink-downlink configuration in the LTE radio communication. The authors argue that their mechanism is capable of determining the best configuration based on the traffic dynamics from the hybrid network, offering significant network improvements in terms of jitter and latency.

An AI architecture which is used to model or approximate objective functions for existing models or to create accurate models that were impossible to represent in the past without the intervention of learning machines, is ANN. ANNs have been proposed to solve propagation loss estimation in dynamic environments, where the input parameters can be selected from the information of the transmitter, receiver, obstacles like buildings, frequency, and so on, and the learning network will train on that data to learn to estimate the function that best approximates the propagation loss for next-generation wireless networks [15-18]. In the same context, Ayadi et al. [19], proposed a Multi-Layer Perceptron (MLP) architecture to predict coverage for either short or long distance, in multiple frequencies, and in all environmental situations. The MLP presented uses feed-forward training with back propagation to update the weights of the ANN. They used the inputs of the ITU-R P.1812-4 model [20], to feed their network composed by an input layer, a hidden layer, and one output layer. They showed that the ANN model is more accurate to predict coverage in outdoor environments than the ITU model, using the standard deviation and correlation factor as a comparison measure. Among other AI techniques with potential for wireless communications, there are K-Nearest Neighbors, Logistic Regression, Decision Trees and Random Forests.

3 Unsupervised learning in 5G mobile and wireless communications technology

According to work [21], in unsupervised learning, no labels are given to the learning algorithm and structure in its input should be found on its own. Self-Organizing Map (SOM) is an example that is trained using unsupervised learning. In SOM, unlabeled data are fed in to a neural network to produce a low-dimensional (usually two-dimensional), discretized representation of the input space of the training samples, called a map (as illustrated in Figure 2), and is therefore a method to do dimensionality reduction.

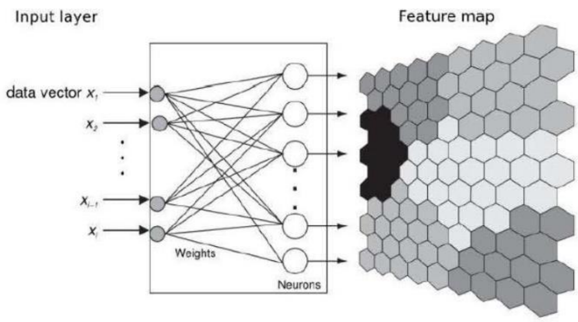

Fig. 2. Example of unsupervised learning: self-organizing Network [21].

In unsupervised learning, the system attempts to learn without any guidance. This technique is particularly useful when we want to detect groups of similar characteristics. At no point, we tell the algorithm to try to detect groups of related attributes; the algorithm solves this connection without intervention. However, in some cases, we can select the number of clusters we want the algorithm to create. Balevi et al. [21], incorporated fog networking into heterogeneous cellular networks and used an unsupervised soft- clustering algorithm to locate the fog nodes that are upgraded from Low Power Nodes (LPNs) to High Power Nodes (HPNs). The authors showed that by applying machine learning clustering to a priori known data like the number of fog nodes and location of all LPNs within a cell, they were able to determine a clustering configuration that reduced latency in the network. A typical unsupervised learning technique is K-means clustering; numerous authors have investigated the applications of this particular clustering technique in the next generation wireless network system.
AI for SON: Automatic root cause analysis. Self-Organizing Networks (SONs) establish a new concept of network management which provide intelligence in the operation and maintenance of the network. It has been introduced by 3GPP as a key component of LTE network. In the 5G era, network densification and dynamic resource allocation will result in new problems for coordination, configuration and management of the

network, hence bringing increased demand for the improvements of the SON functions. SON modules in mobile networks can be divided into three main categories: self-configuration, self-optimization and self-healing. The main objectives of SON are to automatically perform network planning, configuration and optimization without human intervention, in order to reduce the overall complexity, Operational Expenditure (OPEX), Capital Expenditure (CAPEX) and man-made faults. Various researches of AI in SON have been summarized in [32,34] which includes AI applied in automatic base station configuration, new cell and spectrum deployment, coverage and capacity optimization, cell outage detection and compensation, etc., using approaches including ANN, ant colony optimization, genetic algorithm, etc.

In this section, we introduce the automatic root cause analysis framework proposed in [35] as an example for AI in SON. The design of the fault identification system in LTE networks faces two main challenges: (1) A huge number of alarms, KPIs and configuration parameters can be taken as fault indicators in the system. Meanwhile, most of the symptoms of these indicators are not labeled with fault causes, hence are difficult to identify; (2) The system is not automatic and experts are involved to analyze each fault cause. With the huge amount of high-dimensional data, human intervention is not efficient while expensive. Authors of [35] proposes an AI-based automatic root cause analysis system which combines supervised and unsupervised learning techniques as summarized in the following steps:

1. Unsupervised SOM training. SOM is applied for an initial classification of the high-dimensional KPIs. An SOM is a type of unsupervised neural network capable of acquiring knowledge and learning from a set of unlabeled data. It will process high-dimensional data and reducing it to a two-dimensional map of neurons that preserves the topological properties of the input data. Hence, inputs close to each other will be mapped to adjacent neurons.

2. Unsupervised clustering. After SOM training, all the neurons in the SOM system will be clustered into a certain number of groups using an unsupervised algorithm. Since the SOM neurons are already ordered and the difference between the original inputs can be represented by Euclidean distance between the corresponding neurons.

   Labeling by Experts. After the above two steps, the original high-dimensional data are clustered into several classes. We will finally have the experts to analyze and identify the fault causes of each obtained cluster to have all the clusters labeled. With the training, clustering and labeling, an automatic system for network diagnosis is constructed by the workflow shown in Figure 3. For a new input of KPIs, it will firstly be mapped to a neuron in SOM. Then by the label of the cluster this neuron belongs to, we can identify the fault and the causes. After obtaining a certain amount of new fault data, we can verify whether the system is right or not and update it by re-training with the above three steps.

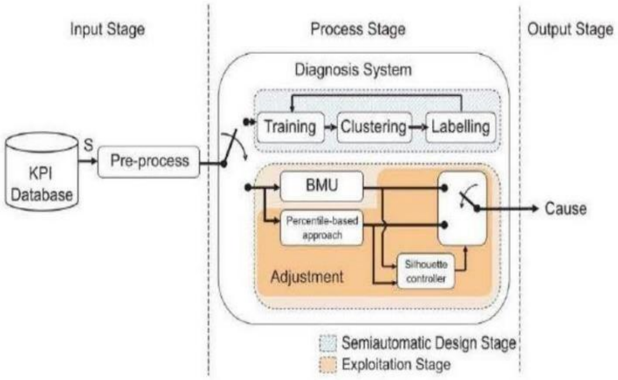

Fig. 3. Automatic root cause analysis workflow [23]

In [23], the authors discussed how K-means clustering algorithm and its classification capabilities can aid in selecting an efficient relay selection among urban vehicular networks. The authors investigated the methods for multi-hop wireless broadcast and how K-means is a key factor in the decision-making and learning steps of the base stations, that learn from the distribution of the devices and chooses automatically which are the most suitable devices to use as a relay.

4 Reinforcement learning in 5G mobile and wireless communications technology

This technique is based on alternative interaction between Agent and Environment and the process is illustrated in Figure 4. The Agent will perform certain action and as a result of this action his state will change which leads to either a reward or a penalty. The Agent will then decide the next action based on this result. By iterating through action and reward/penalty process, Agent learns the Environment.

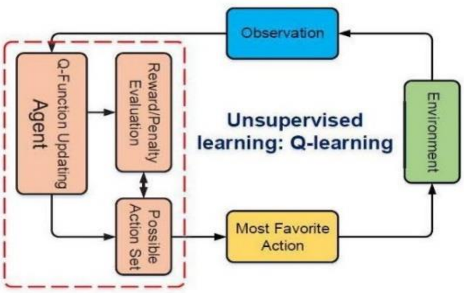

Fig. 4. Reinforcement learning: Q-learning [5].

The philosophy of Reinforcement Learning scheme is based on a learning system often called agent, that reacts to the environment. The agent performs actions and gets rewards or penalties (negative rewards) in return for its actions. That means that the agent has to learn by itself creating a policy that defines the action that the agent should choose in a certain situation. The aim of the reinforcement-learning task is to maximize the aforementioned reward over time [5, 13].

5 CONCLUSION

The advent of 5G is introducing new challenges for mobile communications service providers, and integrating AI techniques into networks is one way the industry is addressing these complexities. AI is already being incorporated into networks, with a primary focus on reducing capital expenditure, optimizing network performance and building new revenue streams.AI will be vital for improving customer service and enhancing customer experience. The 5th wireless communication (5G) techniques not only fulfil the requirement of increasing the internet traffic in the next decade, but also offer the underlying technologies to the entire industry and ecology for internet of everything. The resurgence of artificial intelligence techniques which is possibly superior over traditional ideas and performance, offers as an alternative option. Compared to the existing mobile communication techniques, 5G techniques are more-widely applicable and the corresponding system design is more complicated. Potential research directions to which AI can make promising contributions need to be identified and evaluated. This overview paper first combs through promising research directions of AI for 5G, based on the understanding of the 5G key techniques. This work also devotes itself in providing design paradigms including optimal resource allocation, 5G network optimization, end-to-end physical layer joint optimization, 5G physical layer unified acceleration, and so on.

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