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Machine Learning for 5G

BehnazBagherian
Faculty of Computer Science, University of Putra Malaysia

KhashayarHassanifeizabadi
City University Business School

Abstract__*Deployment of 4G / LTE mobile network has solved the great challenge of high capacity to create real mobile broadband Internet. This was made possible mainly by a robust physical layer and a flexible network architecture. However, bandwidth-hungry services have been developed unprecedentedly, such as virtual reality, augmented reality, etc. In addition, mobile networks with other new services are in strong demand for higher reliability and near-zero latency performance. Such as vehicle communications or vehicle internet. 5G has overcome some of these challenges. In addition, the adoption of software defense networks and virtualization of network functions has added a greater degree of flexibility to operators, allowing operators to support high-demand services from different vertical markets. However, network operators have to consider a higher level of intelligence in their networks to have a deep and accurate understanding of the operating environment and the behaviors and needs of users. It is also essential to predict its evolution to actively and efficiently create an (self) scalable network. This chapter explains the role of artificial intelligence and machine learning in 5G and beyond to build a cost-effective and compatible next-generation mobile network. Some practical applications of AI / ML in the network lifecycle are discussed.*

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I. INTRODUCTION

In 5G wireless communication systems, making the most of valuable bandwidth, power, and antenna resources has become a critical topic in recent studies.The official 3GPP standardization organization recently published the official standard and added key features to improve system performance and reduce latency[1].The goal of 5G is to extend bandwidth and make flexible use of system resources to achieve better performance; resources in time, spectrum, and spatial domain are combined and optimized together[2].

Traditional 5G studies mainly deal with mathematical limit testing and then provide heuristic methods to approximate the tested limit. However, there are hardly any effective operations to reach the limit considering only the coding, modulation, antenna selection, etc.

To solve this problem, the researchers tried to introduce the famous technology of machine learning (ML), deep learning (DL), and artificial intelligence (AI)[3-5]. The growing discussions about deep learning in AI have provided opportunities to improve system performance in 5G-related jobs. Resource allocation benefits could be realized using the dedicated neural network based on the deep learning study process. So, there is still plenty of room to approximate the theoretical limit using resource allocation[4].

II. 5G

Fifth-generation (5G) wireless technology is the latest version of cellular technology designed to increase the speed and responsiveness of wireless networks significantly. With 5G, data transmitted over wireless broadband connections can travel at speeds of several gigabits, with potential maximum speeds of up to 20 gigabits per second (Gbps) by some estimates. These speeds exceed wired network speeds and offer latency of 1 millisecond (ms) or less, which is helpful for applications that require real-time feedback. 5G will allow a sharp increase in the amount of data transmitted over wireless systems due to more available bandwidth and advanced antenna technology. [6-8]

5G networks and services will be rolled out in stages over the next few years to accommodate the increasing reliance on mobile and internet-enabled devices. Overall, 5G is expected to spawn various new applications, uses, and business cases as the technology is rolled out[9,10].

III. Capable of 5G

5G will do much more than significantly improve your network connection. It opens up new opportunities, offering innovative solutions that reach society. Imagine billions of connected devices collecting and sharing information in real-time to reduce traffic accidents, or applications that save lives and that can take off thanks to guaranteed connections without delays, or production lines so predictive that they can prevent outages long before they occur. Fig. 1 shows the capability of 5G[11,12].

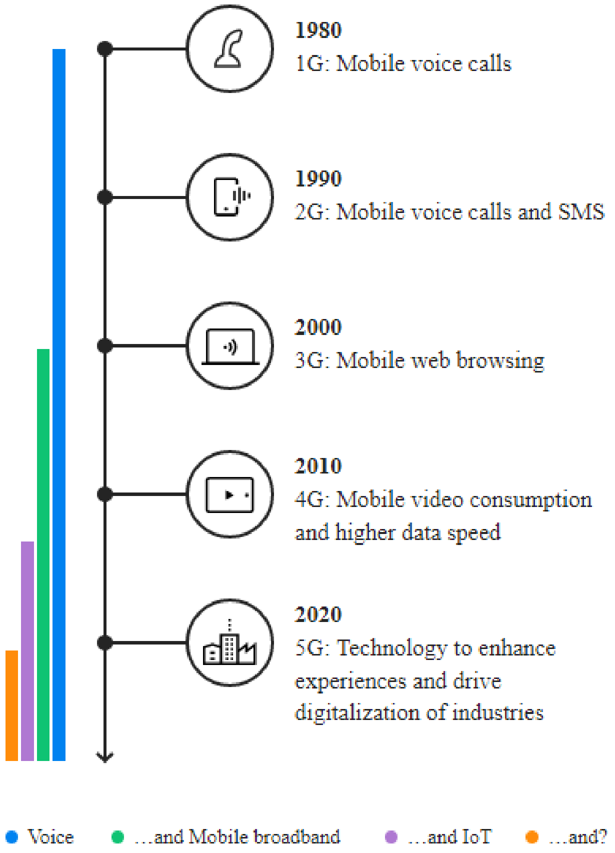

Fig. 1. capable of 5G

IV. Machine Learning

Simply put, machine learning (ML) is a subset of artificial intelligence that creates algorithms and statistical models to perform a particular task without using explicit instructions based on patterns and inferences. ML algorithms use mathematical models based on sample data, training data to predict or make decisions without special planning [13-15]. Learned signal processing algorithms can enable the next generation of wireless systems by significantly reducing power consumption and improving density, power, and accuracy compared to today's fragile systems and manual design. Deep learning is a subset of machine learning in which the algorithms used to have different levels, each offering a different interpretation of the data [16]. The upcoming network of algorithms is known as artificial neural networks because it is very similar to the neural networks of the human brain.With the potential of using ML and AI to integrate into 5G networks, industries are now working towards innovation with 5G. Some of the main innovations on this horizon are:

- **Sports:** Advanced 5G display features such as 3D display and various elements provide the perspectives of a live game.
- **Wireless Virtual Reality (VR):** With 5G, users can enjoy virtual reality content anywhere, anytime.
- **5G Augmented Reality:** (AR) offers realistic AR services such as virtual zoos.
- **Live performances:** 5G offers excellent high-quality performance from wireless devices.
- **Game** streaming**:** games are processed in the cloud via 5G and streamed as long as allowed
- Singing Online **-** Many people can sing online using 5G capabilities.
- **Self-driving cars:** This technology requires computing power that can only be achieved through 5G networks and artificial intelligence, as 3D city maps are uploaded to vehicles in real-time, traffic is updated, and software updates are performed through it.

- **5G uses industry-**standard RAN waveforms, such as "5G New Radio Interface Air" developed by the International 3GPP Committee. To achieve 5G performance improvements, DeepSig'sOmniPHY supersedes AI 3GPP 5G processing algorithms while maintaining compatibility. Available.
- **Deeping's advanced algorithms** in 5G RAN help reduce power, lower component costs, increase device density and performance, and make 5G BTS more efficient. Deployment is cheaper and more independent in OpEx and CapEx terms.
- **Deeping invests** heavily in using AI for 5G and other consumer wireless technologies and is rapidly developing, exploring, and manufacturing these capabilities with OmniPHY software.
- **Wireless Home -** Some older 5G devices have whole-house wireless hotspots.
- **Low-cost scanners**, such as farm-specific equipment, ATMs, medical equipment, and heavy-duty remote control machines - these do not require a permanent connection and willpower, so you can work on the same battery for 10 years without leaving to send data periodically. Technicians with specialized skills will work with machines from anywhere in the world.
- **Public infrastructure and security:** Cities and other municipalities can be more active with the effective use of 5G networks. Utilities will be able to track sensors remotely. They can alert public works when garbage floods or street lights go out, and offices will be able to install surveillance cameras quickly and inexpensively.
- **Healthcare:** Telemedicine, telemedicine, AR physical therapy, precision surgery, and even remote surgery are possibilities. Hospitals can set up sensor networks to monitor patients, doctors can prescribe smart pills to track compliance, and insurers can monitor subscribers to determine appropriate treatment options.

V. Deep Learning

Deep learning is a type of machine learning and artificial intelligence (AI) that mimics the way humans obtain certain types of knowledge. Deep learning is an essential element of data science, including statistics and predictive modeling. It is highly beneficial for data scientists tasked with collecting, analyzing, and interpreting large amounts of data; Deep learning makes this process faster and more accessible [17-19].

Deep learning can be thought of as automating predictive analytics in its simplest form. While traditional machine learning algorithms are linear, deep learning algorithms stack up in a hierarchy of increasing complexity and abstraction. Imagine a young child whose first word is a dog to understand deep learning. The young child learns what a dog is and is not by pointing to objects and saying dog[20]. The parent says, "Yes, that is a dog" or "No, that is not a dog." As the child points to objects, he becomes more aware of all dogs' characteristics. What the young child does, unknowingly, is clarify a complex abstraction, the concept of dog, by building a hierarchy in which each level of abstraction is created with knowledge gained from the previous layer of the order. Fig.2 shows the difference of deep learning and machine learning[21-23].

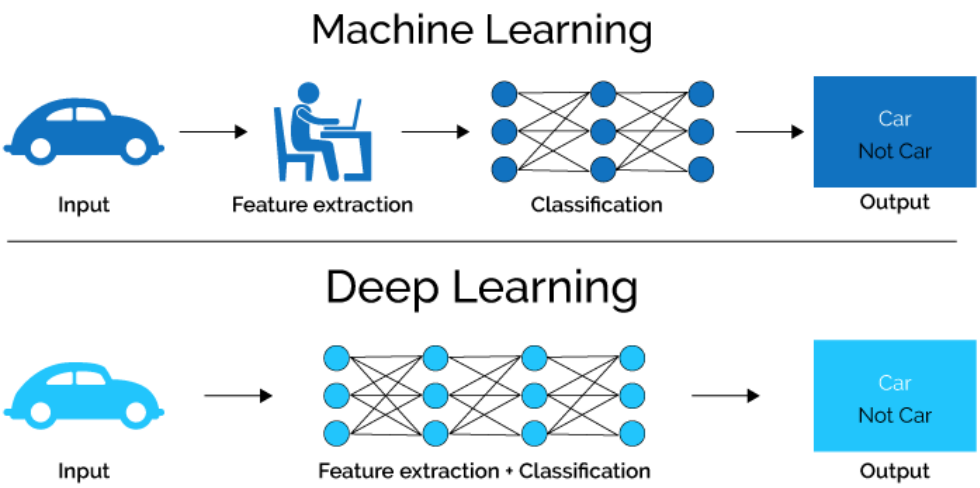

Fig.2. difference of deep learning and machine learning

a) Machine learning / deep learning in 5G

With the increasing advancements and advantages of ML in wireless communications, each research community has tried to assess the impact of ML in 5G on their discipline[24]. As a result, we have several posts for the effect of ML on the physical layer, security aspects, radio resource management.It makes it very difficult to give a brief overview of the use and impact of AI / ML in 5G. Therefore, we can summarize the works applying ML to 5G according to two principles: a "general ML categorization", where we consider all possible ML approaches from the literature, and a "Deep learning-based categorization," which is focused only on deep learning. , because several leading publications consider deep learning as the most promising ML approach to the high complexity of 5G[25]. A general categorization of ML in the case of 5G follows the general structure of ML as seen in the first sections, which uses three kinds of ML: supervised learning, unsupervised learning, and reinforced learning. Table 1 shows an example of this classification with the learning approaches used in each class and a concrete example of application in 5G, [26]. Some 5G use cases will be described in the next section, and a solution for AI / ML integration in mobile network operators will be proposed[27].

Table 1: Learning approaches and their 5G applications for the three ML classes.

Learning classes	**Learning models**	**Example of applications in 5G**
Supervised learning	ML and statistical logistic regression techniques.	Dynamic frequency and bandwidth allocation in self-organized LTE dense small cell deployments
	Support Vector Machines (SVM)	Path loss prediction model for urban environments
	Neural-Network-based approximation	Channel Learning to infer unobservable channel state information (CSI) from an observable channel
	Supervised ML Frameworks	Adjustment of the TDD Uplink-Downlink configuration in XG-PON-LTE Systems to maximize the network performance based on the ongoing traffic conditions in the hybrid optical-wireless network
	Artificial Neural Networks (ANN), and Multi-Layer Perceptrons (MLPs).	Modeling and approximations of objective functions for link budget and propagation loss for next-generation wireless networks
Unsupervised Learning	K-means clustering, Gaussian Mixture Model (GMM), and Expectation-Maximization (EM).	Cooperative spectrum sensing and Relay node selection in vehicular networks.
	Hierarchical Clustering.	Anomaly/Fault/Intrusion detection in mobile wireless networks
	Unsupervised Soft-Clustering ML Framework.	Latency reduction by clustering fog nodes automatically decides which low power node (LPN) is upgraded to a high power (HPN) in heterogeneous cellular networks.
	Affinity Propagation Clustering.	Data-Driven Resource Management for Ultra-Dense Small Cells
Reinforcement Learning	Reinforcement Learning algorithm based on long short-term memory (RL-LSTM) cells.	Proactive resource allocation in LTE-U Networks is formulated as a non-cooperative game, enabling SBSs to learn which unlicensed channel, given the long-term WLAN activity in the channels and LTE-U traffic loads.
	Gradient follower (GF), the modified Roth-Erev (MRE), and the modified Bush and Mosteller (MBM).	Enable Femto-Cells (FCs) to autonomously and opportunistically sense the radio environment and tune their parameters in HetNets, to reduce intra/inter-tier interference.
	Reinforcement Learning with Network-assisted feedback.	Heterogeneous Radio Access Technologies (RATs) selectio

b) machine learning important for 5G wireless systems

Existing 4G networks use Internet Protocol (IP) broadband connectivity to transmit, offering poor efficiency. ML and AI enable 5G networks to be predictive and proactive, essential for 5G networks to become functional. By integrating ML into 5G technology, smart base stations will make decisions for themselves, and mobile devices will create dynamically adaptive clusters based on learned data. This will improve network applications' efficiency, latency, and reliability [29,30].

VI. ML / DL Potentials For 5G Communications

As the 5G network becomes more and more complex and novel uses emerge, such as autonomous cars, industrial automation, virtual reality, electronic health, and others, ML will become essential to make the 5G vision a reality. As with any new technology, there are significant potentials to be achieved and limitations to overcome. Fig.3 shows the Potentials For 5G Communications[18].

❖ **Enhanced Mobile Broadband (eMBB) -** Enables new applications with higher data rate demands in a uniform coverage area. Examples include ultra-high-definition video streaming and virtual reality.

❖ **Massive Machine Type Communications (mMTC) -** A key feature of 5G communication services is the demand for scalable connectivity to expand the number of wireless devices with efficient transmission of small amounts of data in extended coverage areas. Applications such as body area networks, smart homes, IoT, and drone delivery will generate this type of traffic. The mMTC must be able to accommodate new and even unforeseen uses.

❖ **Ultra-Reliable Low Latency Communications (URLLC)-** Connected healthcare, remote surgery, mission-critical applications, autonomous driving, vehicle-to-vehicle (V2V) communications, high-speed rail connectivity, and intelligent industrial applications prioritize reliability, low latency, and mobility over data rates.

Fig.3.ML/DL Potentials For 5G Communications

a) Limitation of ML / DL limitations for 5G communications

- **Data:** High-quality **data** is essential for machine learning applications, and the type of data (tagged or unlabeled) is crucial in deciding what kind of learning to use. ML is only as good as the data it receives.
- **No Free Lunch Theorem:** This theorem states that if all possible data-generated distributions are averaged, each ML algorithm will have the same performance in inferring unobserved data. This means that the goal of ML is not to search for the best learning algorithm but to understand what type of distribution is relevant to a specific 5G application and which ML algorithm performs the best on that particular data.
- Hyperparameter **selection:** Hyperparameters are values set in ML algorithms before training begins. These values must be selected with care because they influence eventual parameters updated from the learning results.
- **Interpretability vs. Accuracy:** From a stakeholder point of view, the complex interactions between independent variables can be challenging to understand and do not always make business sense. Therefore, a trade-off must be made between data interpretation and overall precision.
- **Privacy and security:** ML algorithms can be subject to contradictory attacks, such as modifying an input sample to force a model to classify it in a different category from its genuine class.

VII. Conclusion

We have seen that ML has enough value to dream and experiment with the future in which ML can be an inherent element of wireless communication. However, to adopt ML in 5G / B5G, it must be borne in mind that ML cannot be applied everywhere, given the cost, time, latency, and latency introduced by some ML techniques with some applications in time. The total distance. ML and 5G as a discipline together have a lot of room for improvement. Until the large telecommunications industry fully trusts ML, the pace of development in this area will be considerable due to the need for precision and not breaking current systems. Attention will be limited. Since ML can add uncertainty and complexity to any network, our enthusiasm must be very carefully diminished.

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