ROLE OF DEEP LEARNING ANALYTICS IN WIRELESS NETWORKS

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Abstract

The first method for implementing this mobile AI paradigm is to treat each device in the network as a rational and autonomous decision-maker, which acquires its own local dataset and uses it to create its own local ANN model. In terms of data sharing and processing, this method eliminates the need for network infrastructure and edge users to communicate, and it has the ability to make the 5G vision of distributed, self-managing networks a reality. Although mobile devices may not be able to construct accurate models on their own, the ensuing difference in performance must be examined because of the restricted storage and processing capabilities they have. As a result, it's unclear whether or not a stable network operating point can be reached, let alone whether or not it's efficient. One method to answer the final two questions is to use the Noble-prize-winner framework of game theory, which gives sophisticated numerical tools for analysing the interactions among independent decision makers in games of chance. Game theory has already been extensively employed in wireless communication networks, but it has never been applied in conjunction with deep learning.

Keywords:

Data Analytics, Wireless Network, Deep Learning

1. INTRODUCTION

The combination of AI-capable nodes and a data-driven network paradigm is necessary to create an intelligent wireless network because the necessity of an intelligent wireless network necessitates that each network segment be equipped with AI capabilities. However, while this certainly reduces the need for mathematical models for network design and operation, it does not necessarily indicate that traditional mathematics-oriented models and approaches should be rejected. In fact, we believe that combining model-based and AI-based strategies can provide significant benefits, and we anticipate future wireless networks in which these two approaches function in concert.

But how do we create wireless networks that are intelligent and self-aware? Machine learning, in particular deep learning, is a framework that allows this to happen. Computers can learn from data rather than being explicitly programmed thanks to machine learning techniques [1]. For communication systems, machine learning techniques are not new, and numerous machine learning approaches have been developed and suggested, including support vector machines, decision trees, Bayesian networks, genetic algorithms, and rule-based learning, among others.

For further information on machine learning and wireless networks, see [2]–[4], where detailed surveys and tutorials are available, and [5], where SON networks are discussed. The communication community has just lately begun to pay attention to deep learning [6]–[9], the most prominent machine learning technique in many sectors of science.

Deep learning is a machine learning technique that uses artificial neural networks (ANNs) to implement the learning process of elaborating the data (ANNs). Section II will describe in further detail how ANNs make deep learning more effective than other machine learning techniques, especially when there is a lot of data available. Due to its dominance in several scientific domains, including image classification, text recognition, speech recognition, audio and language processing, and robotics, deep learning has risen to the top of the list of the top ten AI technological trends for 2018 [10]. But despite all of this, as previously stated, its use in communication systems has only been envisioned recently [11], and its potential is currently largely untapped. One reason for this is that communication engineers have traditionally relied on mathematical models to build systems rather than data-driven techniques, which we believe is the primary reason for this shift. However, as we've seen, this fundamental tenet will be challenged in the near future, necessitating the development of communication systems that are adept at deep learning. Due to recent technological breakthroughs, deep learning is now a viable solution for future communication networks. To put it more succinctly:

- A huge dataset is required in order to get the most out of deep learning algorithms. Currently, as the number of wireless devices grows exponentially, so does the amount of traffic data.
- Because of recent advances in computing power, larger and more sophisticated algorithms can now be executed considerably more quickly. As an example, GPUs may be repurposed to run deep learning algorithms at speeds that are many times faster than regular processor chips.

Several major telecommunications companies have recently advocated for the use of deep learning in communications [12], [13]. There have already been some preliminary moves toward the standardisation of intelligent wireless communication networks. According to the European Telecommunications Standards Institute (ETSI), a new Industry Specification Group called Experiential Network Intelligence has been formed with the goal of developing a cognitive network management framework that can adapt services based on changing user needs, environmental conditions, and business objectives by utilising AI techniques and context-aware policies. As a first step towards the definition of an experiential system, the observe-orient-decide-act control paradigm describes a system that learns from its past experiences in order to increase its knowledge of how to behave in the future. Automated network configuration and monitoring methods are expected to save operational costs and improve network use and maintenance.

The International Telecommunication Union (ITU) has launched a standardisation initiative for machine learning in future mobile networks, which aims to define an architectural framework for machine learning in future networks, define the integration of machine learning functionalities into future mobile network architectures, and identify techniques for network management in future wireless environments.

2. RELATED WORKS

Some problems must also be overcome in order to realise the goal of AI-based wireless networks. Among today's most pressing issues, two stand out:

Even though it is evident that future communication networks will require AI, it is not clear how ANNs should be integrated into the communication network architecture. A single ANN should be responsible for a broad network domain, or should each network device store its own data and run a local ANN, depending on how much information is available?

We believe it is important to emphasise that machine learning is expected to be a game changer not only for mainstream wireless communication networks, but also for emerging communication technologies that are being investigated as a way to supplement traditional wireless approaches in certain scenarios.

Optic wireless communications, which use visible light to communicate at high speeds, and molecular communications, which use chemical signals as information carriers instead of electromagnetic waves, are just two examples of emerging technologies that promise to revolutionise how we communicate in places like water, inside our bodies, and even through the walls of buildings.

Both technologies have attracted a lot of attention recently, but they both have the problem of being hard to model mathematically. Since models aren't needed in these systems, AI-driven techniques, like the one used in [13], which uses deep learning to solve Schrodinger equations for fiber-optic communication, can make a significant contribution to their practical implementation.

3. RESOURCE MANAGEMENT

We believe it is no longer sufficient to rely exclusively on wireless networks whose logical operation is software-controlled and tuned to meet these tough requirements. An intelligent software-reconfigurable entity [4] needs to be created for the wireless environment itself, whose operation is optimised to ensure continuous communication. Smart environments, i.e., wireless environments that can be reconfigured to operate as active spaces for the transfer and processing of information, are required for future wireless networks. “Smart radio environment” [11] is a term we use to describe this new wireless reality.

Consider the block architecture in Fig.1 to further understand our concept of a programmable and adaptable wireless environment. Here's how present wireless networks differ from a smart radio environment, conceptually. System models are supplied and formulated in terms of transition probabilities according to Shannon [8].

However, according to Wiener [9], the output of the system model is still presented, but it is optimised by taking the output into consideration. For channel-aware beamforming, for example, the receiver sends the channel status back to the emitter. As part of a “smart radio” setup, the surrounding objects can detect and give back the system's response to radio waves (the actual physical world) and digital waves (the digital world).

The software controller optimises and configures the input signal and the response of the environmental objects to radio waves, respectively, based on the detected data. Phase shifts can be used to direct the signal's path to a specific target, such as a certain object in the surroundings. As a result, the incoming signal is guided toward the receiver.

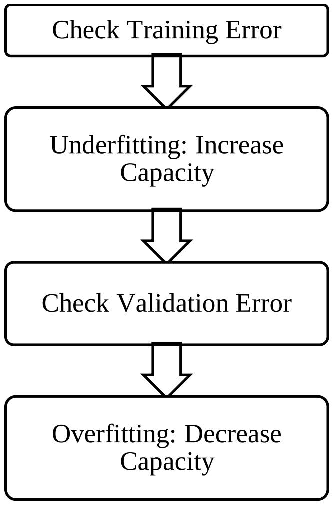

Fig.1. Workflow of Resource Scheduling

The purpose of resource management is to maximise one or more performance indicators by allocating network resources. In order to maximise network throughput, communication latency, and energy efficiency, network terminals can be scheduled based on the traffic demands, propagation channel conditions, and the requirements of the end-users, so as to ensure that all end-users experience the guaranteed quality-of-service (QoS). Formally, the resource allocation problem can be represented as an optimization algorithm by denoting f as the performance function to optimise and allocating as the resource to use.

As a result, standard optimization theory techniques are at the heart of the conventional approach to resource management. Although this method works if an appropriate mathematical model of the problem can be developed, it requires the development of tractable yet accurate formulas to describe the objective f and the feasible set S. The presence of multi-user interference makes most relevant radio resource allocation problems NP-hard in interference-limited systems.

As an example, in interference-limited networks, power allocation for sum-rate maximisation is known to be NP-hard [7], which implies that beamforming and energy efficiency maximisation problems are also NP-hard [3]. If we could solve the NP-hard issue at a reasonable cost, the optimal resource allocation would still depend on the system parameters, such as how many users are connected, how many channels are used, and how rapidly they fade.

A new optimization issue must be solved every time one of these parameters shifts, which happens frequently in mobile situations. In big and sophisticated systems, such as future wireless communication networks, this leads to high complexity overhead that restricts the real-time application of available optimization frameworks.

All of these problems are exacerbated in smart radio situations because the number of variables to be optimised greatly exceeds the typical figures. With the help of ANNs and deep learning, it is possible to achieve true online resource management in this environment. When it comes to designing wireless networks, deep learning has been used for the first time to illustrate its potential.

Because the general resource allocation problem in (1) can be viewed as an unknown function mapping from an ensemble of all relevant network parameters

Problem 1 can be transformed into the problem of learning an unknown map, which ANNs are capable of accomplishing. Although it is not stated explicitly, ANNs are universal approximators in that they can learn the input-output relation between system parameters and desired resource allocation, simulating the function F. These results show that we can maximise a desired performance function without directly solving any optimization problem, but rather by allowing an ANN to compute the resource allocation for us.

4. PERFORMANCE EVALUATION

A reasonable follow-up to this consideration is to ask how to integrate ANN-based resource management into the wireless network's topology and architecture. Ideally, a cloud-based strategy would use an "artificial brain" positioned at a single point to oversee the entire network or at least a section of the network in terms of resource management activities. It is imperative that all accessible data be gathered and stored in this artificial brain, which will be tasked with doing all necessary computations and relaying the ideal resource allocation strategy to all other network terminals. For at least three primary reasons, such a centralised strategy is incompatible with future wireless networks.

- **Latency**: End-to-end communication delays must be less than a millisecond in some vertical sections of future wireless networks. As a result, waiting for the cloud to complete computations before sending the results to end users is not an option for these apps. Instead, the computations might be handled locally, on the computers of the consumers.
- **Privacy**: Future wireless networks, unlike previous generations, will not be limited to achieving faster mobile networks or providing richer functionality in smartphones. Innovative vertical service integration aspires to make the "everything linked world" a reality, but this comes with significant privacy and security considerations.
- Consequently, cloud-based deep learning is not a convenient approach for some vertical applications because sharing information with the cloud is not acceptable. However, even though network security mechanisms exist and provide us with privacy, integrity, and authentication, their use has a cost in terms of added complexity and data transmission.
- The use of specific cryptographic algorithms, such as Advanced Encryption Standard (AES) and Rivest-Shamir-Adleman (RSA), which run on top of the physical layer and require the execution of finite field operations on each block of transmitted data, is required by commercial solutions for privacy and/or authentication.
- Aside from the use of hash codes, which require certain processes to construct the hash code for each packet of transmitted bits, data integrity is often ensured by using these codes. Large-scale networks may see a significant drop in communication performance as a result of these additional costs. Furthermore, end users will have a higher level of trust in the system because no sensitive data needs to be sent.
- **Connectivity**: In the future, wireless networks will be able to provide ubiquitous service. User terminals must be able to work even in regions or times where the cloud connection is weak. Cloud-based implementations can't meet this requirement, so each user device needs some "local intelligence" to work in these situations as well.

5. CONCLUSION

This means that deep learning cannot be restricted to a single network node in order to be compatible with the next generation of wireless communication networks. Instead, a mobile AI architecture, which distributes intelligence among mobile devices on a network, is needed. When we think about how human knowledge is developed, it is interesting to note that the mobile AI paradigm envisions both a cloud intelligence that every node of the network can access via the cloud and a device intelligence that is unique to each network device. This approach is similar to how human societies are built.

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