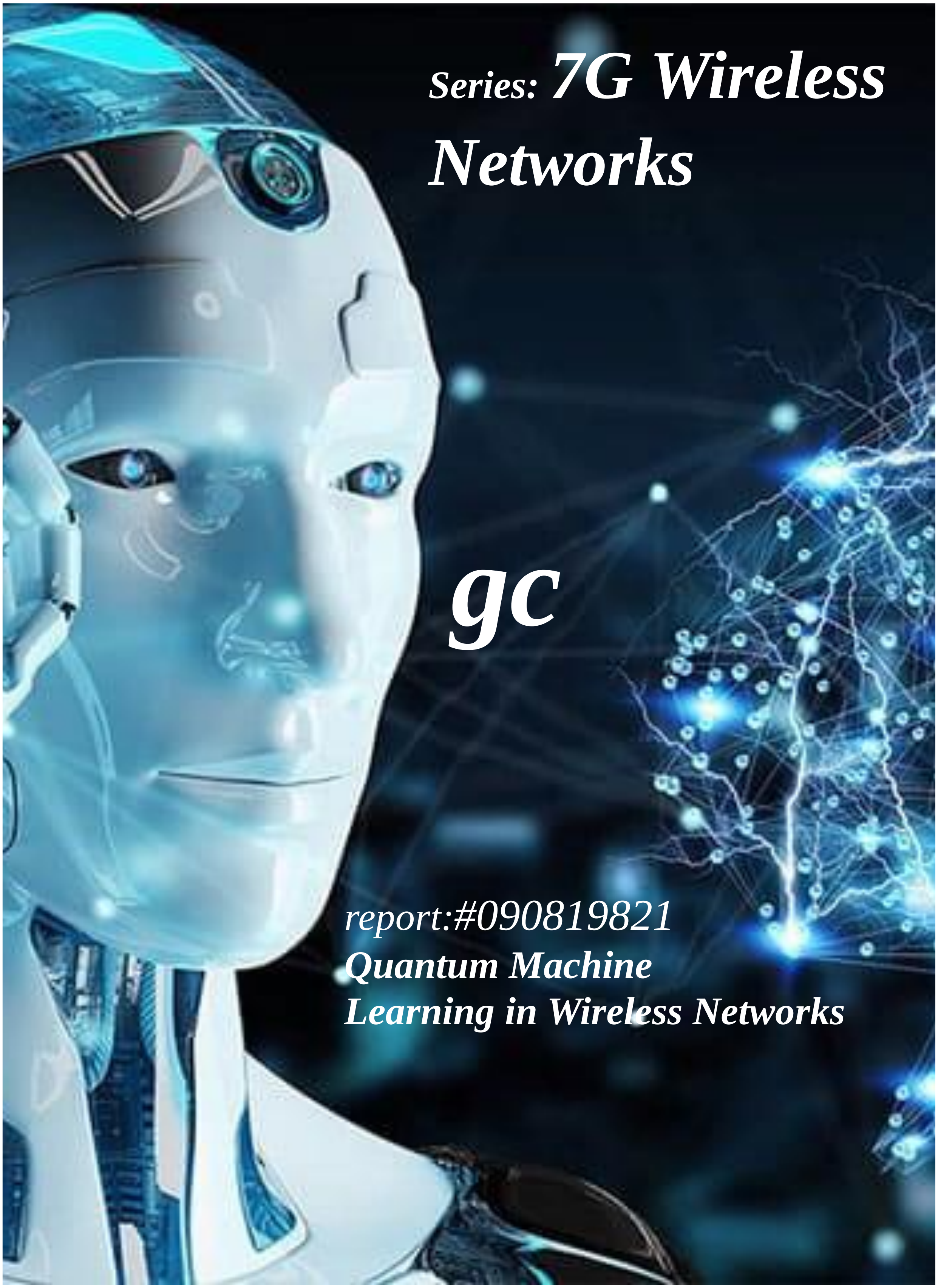

Series: ***7G Wireless Networks***

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report:#090819821

Quantum Machine Learning in Wireless Networks

series: ***7G Wireless Networks***

report: #090819821 ***QUANTUM MACHINE LEARNING***

by Savo Glisic
Worcester Polytechnic Institute, Massachusetts

GC Institute for Networking Science

Preface

As a part of the solution to the constant demand for higher data rates, wireless communications are moving towards higher and higher frequencies including mmWave and THz bands. At the same time quantum physics is experimenting with quantum state transmission over sub-optical, THz and even much lower bands. In the anticipation of the development of quantum computer networks and quantum key distribution QKD over wireless networks, there is a need for design tools that will enable optimization of the heterogeneous networks that will seamlessly merge these two technologies as much as possible. At the same time, these networks will relay more and more on artificial intelligence so that further research is needed to integrate classical and quantum machine learning algorithms which is the focus of this report.

In general quantum technology can use either discrete (dv) or continuous (cv) variable information processing, where variables are modeled in the space of finite or infinite dimensions respectively. While the former option, used in our recent book, is used for systematic introduction to the field of quantum computing the latter is more feasible for practical implementation and for this reason is in the focus of this book.

In this series of reports, we make an effort to provide a summary of an impressive work done so far by the quantum physics, computer science and artificial intelligence researchers and elaborate why and how it should serve as a basis for coming up with the solutions for integrated heterogeneous networks as defined above. We believe that 7G wireless networks will be based on this concept although the step-by-step application of this technology is already being proposed for 5G and will be seen in 6G as well.

When it comes to using the report for undergrade and postgraduate courses we incorporate a number of DESIGN EXAMPLES to replace the classical concept of using "problems and solutions" addendums at the end of the chapters/book. This enables using more sophisticated assignments for the teamwork of the students. Our students have shown great enthusiasm for such approach.

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Author *Amherst, Massachusetts*
March 2022

https://www.youtube.com/watch?v=u1XXjWr5frE
https://www.youtube.com/watch?v=j9eYQ_ggqJk

Ch 1 INTRODUCTION

1.1 Structure of the report

We present the overall material of the report within five chapters and in what follows we briefly summarize the content of these chapters.

Ch 2 ADVANCES IN ML: In real life, every experience or decision made, increase the human's knowledge, so that when next time faced with a similar question human can decide more efficiently. On the other hand, ML algorithms described so far have in common that they reset the learning process back to the beginning once they face a new problem to learn. *Lifelong machine learning* (*lifelong ML or LML*) is an advanced machine learning paradigm that learns continuously, accumulates the knowledge learned in previous tasks, and uses it to help future learning. In other words, at any time point, the learner has performed a sequence of N learning tasks, $\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_N$. These tasks, which are also called the *previous tasks*, have their corresponding datasets $\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_N$. The tasks can be of different *types* and from different *domains*. When faced with the $(N+1)$th task $\mathcal{T}_{N+1}$ with its data $\mathcal{D}_{N+1}$, the learner can leverage the *past knowledge* in the *knowledge base* (KB) to help learn $\mathcal{T}_{N+1}$. The objective of LML is usually to optimize the performance on the new task $\mathcal{T}_{N+1}$, but it can optimize on any task by treating the rest of the tasks as the previous tasks. KB maintains the knowledge learned and accumulated from learning the previous tasks. After the completion of learning $\mathcal{T}_{N+1}$, KB is updated with the knowledge gained from learning $\mathcal{T}_{N+1}$. The updating can involve consistency checking, reasoning, and meta - mining of additional higher - level knowledge. A number of related problems and solutions in the implementation of this concept is detailed in this chapter.

Here we also discuss the concept of federated learning as proposed by Google recently. Their main idea is to build machine learning models based on data sets that are distributed across multiple devices while preventing data leakage.

Let us denote by N data owners $\{\mathcal{F}_1, \ldots \mathcal{F}_N\}$, all of whom wish to train a machine learning model by consolidating their respective data $\{\mathcal{D}_1, \ldots \mathcal{D}_N\}$. A conventional method is to put all data together and use $\mathcal{D} = \mathcal{D}_1 \cup \cup \mathcal{D}_N$ to train a model $\mathcal{M}_{SUM}$. A federated learning system is a learning process in which the data owners collaboratively train a model $\mathcal{M}_{FED}$, in which process any data owner $\mathcal{F}_i$ does not expose its data $\mathcal{D}_i$ to others. In addition, the accuracy of $\mathcal{M}_{FED}$, denoted as $\mathcal{V}_{FED}$ should be very close to the performance of $\mathcal{M}_{SUM}$, $\mathcal{V}_{SUM}$. Formally, let δ be a non - negative real number, if $|\mathcal{V}_{FED} - \mathcal{V}_{SUM}| < \delta$ we say the federated learning algorithm has δ - accuracy loss.

Ch 3 DEEP NEURAL NETWORKS: The chapter discusses four relevant topics mainly: Optimization Algorithm Approximation by DNN, Spatial Scheduling by DNN, Spatial Scheduling by DNN with Proportional Fairness and DNN in Vehicular Networks.

Optimization algorithms often entail considerable complexity, which creates a serious gap between theoretical design/analysis and real-time processing. In the first section of the chapter, we present a learning-based perspective to address this challenging issue. The key idea is to treat the input and output of an SP algorithm as an unknown nonlinear mapping and use a deep neural network (DNN) to approximate it. If the nonlinear mapping can be learned accurately by a DNN of moderate size, then SP tasks can be performed effectively—since passing the input through a DNN only requires a small number of simple operations. Here, we first identify a class of optimization algorithms that can be accurately approximated by a fully connected DNN. To demonstrate the effectiveness of the approach, we apply it to approximate a popular interference management algorithm.

The optimal scheduling of interfering links in a dense wireless network with full frequency reuse is a challenging task. The traditional method involves first estimating all the interfering channel strengths and then optimizing the scheduling based on the model. However, this approach is, resource intensive and computationally hard because channel estimation is expensive in dense networks; furthermore, finding even a locally optimal solution of the resulting optimization problem may be computationally complex. In the second section of the chapter, we show that by using a deep learning approach, it is possible to bypass the channel estimation and to schedule links efficiently based solely on the geographic locations of the transmitters and the receivers because in many propagation environments, especially in dense networks, the wireless channel strength is largely a function of the distance dependent path-loss. This is accomplished by unsupervised training over randomly deployed networks and by using a neural network architecture that computes the geographic spatial convolutions of the interfering or interfered neighboring nodes along with subsequent multiple feedback stages to learn the optimum solution. The resulting neural network gives a near optimal performance for sum-rate maximization and is capable of generalizing to larger deployment areas and to deployments of different link densities. To provide fairness, here we present a scheduling approach that utilizes the sum-rate optimal scheduling algorithm over judiciously chosen subsets of links for maximizing a proportional fairness objective over the network. The approach shows highly competitive and generalizable network utility maximization results.

In the previous section, we focus on scheduling with the sum-rate objective, which does not include a fairness criterion, thus tends to favor shorter links and links that do not experience large amount of interference. Practical applications of scheduling, on the other hand, almost always require fairness. In the third section, we first illustrate the challenges in incorporating fairness in spatial deep learning, then present a solution that takes advantage of the existing sum-rate maximization framework to provide fair scheduling across the network.

For autonomous driving the freshness (age) of information (AoI) about the vehicular network state is of paramount importance and proper network resource allocation aware of the AoI is the major technical issue in this field. In the fourth section of the chapter we will discuss the problem modelling and possible solutions based on DNN.

Ch 4 QUANTUM MACHINE LEARNING

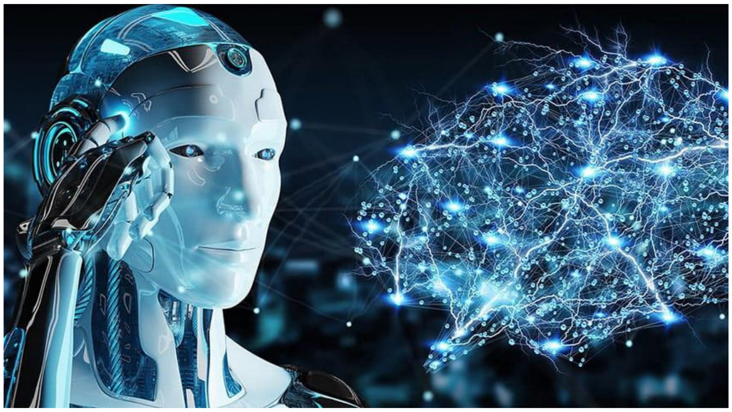
Like the progression of classical deep learning, the first forms of quantum neural networks to be studied were Boltzmann machines. In classical machine learning, some of the work first incorporating backpropagation was in the context of deep networks of coupled spinlike neurons called Deep Boltzmann Networks . On the quantum side, analog quantum computers allowed for a physical implementation of networks of qubits whose statistics mimic those of Boltzmann machines . This general avenue of research focused on determining whether quantum computers can accelerate the training of classical neural network models. Due to the possibility of superpositions of the joint state of the neurons, and thereby of quantum tunneling in the energy landscape, it was hoped that Quantum Annealing could provide a speedup over classical annealing optimization methods for such neural network models. Despite early claims of a speedup , certain bottlenecks such as the embedding problem, qubit quality, and thermal noise would obscure whether there could truly be a quantum advantage for Quantum Annealing, especially with the advent of quantum ‐ inspired classical algorithms designed to compete with these machines.

In this chapter we provide a comprehensive approach to training classical neural networks on a quantum computer for the purposes of classical data learning. All techniques make use of superposition and entanglement, and some techniques employ tunneling directly. We also provide an in ‐ depth analysis of quantum backpropagation of the error signal in these quantum ‐ coherent neural networks, thus explicitly relating quantum and classical backpropagation. The chapter explicitly addresses the problems of: Quantum Neural Networks with DV, Quantum Neural Networks with CV, Quantum Parametric Optimization, Quantum Neural Network Learning, Quantum Parametric Circuit Learning and Quantum Deep Convolutional Neural Networks

Ch 5 REINFORCEMENT LEARNING based QN PROTOCOLS

Considering a quantum network, as opposed to just one line between a sender and a receiver, is a much more complicated setting that leads to questions about, e.g., routing (see Chapter 7 and multicast communication (simultaneous communication between several senders and receivers). Consequently, protocols in a general quantum network can be much more varied than protocols along a linear chain of nodes. As done in classical networking, it is possible to develop a so-called "quantum network stack", which divides the various steps of a quantum network protocol into distinct layers of functionality. Along these lines, quantum network protocols have been described from an information-theoretic perspective in , and limits on communication in quantum networks have been explored . Linear programs, and other techniques for obtaining optimal entanglement distribution rates in a quantum network, have been explored as well.

To physically realize quantum networks, and the quantum internet more generally, the continual challenge is to bridge theoretical statements about what can be achieved to statements that are directly useful for the purpose of implementation. This link between theory and reality should also take into account the limitations of current and near-term quantum technologies, which include imperfect sources of entanglement, quantum memories with relatively low coherence times, and imperfect measurements and gate operations. Many of the theoretical works do not explicitly take these practical limitations into account. What is currently lacking is a formal theoretical framework for quantum network protocols that incorporates both the limitations of near-term quantum technologies and is general enough to allow for optimization of protocol parameters. The purpose of this chapter is to present some efforts to begin such a development. This include discussion on: Quantum Network Protocols, Summary of the analytical tools Quantum Link Layer Protocol, Reinforcement Learning-based quantum decision processes and Quantum Networks.



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