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Course II Report

In the near future, quantum computing is expected to revolutionize the computer science field. The use of quantum bits, also known as qubits, allows computers to store more information than the traditional bits used by most computers today. This allows quantum computers to have greater processing power, and in theory, will allow computer programmers to run algorithms that could not be feasible on a traditional computer, such as Grover's Algorithm and Shor's Algorithm. Quantum computers possessing greater processing power naturally lends itself to improvements in the field of machine learning as well. Quantum machine learning offers many advantages over classical machine learning. A few of the most promising areas of quantum machine learning include simulating quantum feature maps, parameterized quantum circuits, and quantum generative adversarial networks.

Simulating Quantum Feature Maps and Parameterized Quantum Circuits

In machine learning, feature maps are used to convert data so that it can be used for analysis and modeling. By representing data inputs through feature maps, it is easier to detect important trends and features in the data that can help with machine learning. In a quantum feature map, a classical feature vector is mapped to a quantum Hilbert space. Consider, for example, the common red-blue-green (RGB) color descriptions. An RGB value is a classical feature vector–using only three numbers, a specific color can be represented based on the values that correspond to the intensity levels of red, green, and blue, respectively. Classical feature vectors such as an RGB value can be mapped to a quantum Hilbert space, which is a space that has more dimensions than just three (known as Euclidean space). How would mapping a classical feature vector to a quantum Hilbert space lead to an advantage over classical machine learning? Typically, this mapping is done using a parameterized quantum circuit (PCQ). These circuits have the capacity to generate significant subsets of states in the output Hilbert space, and they can entangle qubits, leading to greater advantages. This means it is possible to construct quantum feature maps that are difficult to simulate on a classical computer, demonstrating just one of the many advantages expected to arise from quantum machine learning.

Quantum Generative Adversarial Networks (QGANs)

In classical machine learning, generative adversarial networks are used to train both a generator and a discriminator. For example, a GAN could be represented by a violin teacher assigning students short pieces and having them record themselves playing it, with the goal of trying to emulate a professional player. The teacher must identify between student and professional recordings. In this scenario, the students represent the generator, where they first play poorly but subsequently improve as they receive feedback. The teacher represents the discriminator, where it becomes easier for the teacher to identify student recordings, with more practice identifying flaws in the students' playing. In this way, the teacher and the student work together and both improve, much like a GAN. Quantum Generative Adversarial Networks (QGANs) build upon the concept of GANs by equipping the discriminator or the generator (or both) with PCQs. By utilizing PCQs, the generated data can be represented in quantum states, which are more complex than the values used in classical GANs, giving QGANs an advantage over GANs.

The topics discussed–simulating quantum feature maps, parameterized quantum circuits, and quantum generative adversarial networks–are but three of the many examples of how quantum machine learning can revolutionize the machine learning field. As ongoing research continues to improve quantum computers and reduce errors, computer scientists continue to become increasingly captivated by the possibilities of quantum machine learning.